

## MODELING AND CONTROL OF MULTIVARIABLE DISTILLATION COLUMN USING MODEL PREDICTIVE CONTROL USING UNISIM

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**Abstract** -- Distillation columns are widely used in chemical industry as unit operation and required advance process control because it has multi input multi output (MIMO) or multi-variable system, which is hard to be controlled. Model predictive control (MPC) is one of alternative controller developed for MIMO system due to loops interaction to be controlled. This study aimed to obtain dynamic model of process control on a distillation column using MPC, and to get the optimum performance of MPC controller. Process control in distillation columns performed by simulating the dynamic models of distillation columns by UNISIM R390.1 software. The optimization process was carried out by tuning the MPC controller parameters such as sampling time ( $T_s = 1 - 240$  s), prediction horizon ( $P = 1-400$ ), and the control horizon ( $M=1-400$ ). The comparison between the performance of MPC and PI controller is presented and Integral Absolut Error (IAE) was used as comparison parameter. The results indicate that the performance of MPC was better than PI controller for set point change 0.95 to 0.94 on distillate product composition using a modified model 1 with IAE 0.0584 for MPC controller and 0.0782 for PI controller.

**Keywords:** *model predictive control, multivariable, tuning, distillation column*

**Abstrak** -- Kolom distilasi banyak digunakan dalam industri kimia sebagai unit operasi dan memerlukan proses kontrol terbaru karena memiliki system multi-input multi output yang (MIMO) atau sistem multi-variabel, yang sulit untuk dikendalikan. Model kontrol prediktif (MPC) adalah salah satu pengendali alternatif yang dikembangkan untuk sistem MIMO karena interaksi loop yang harus dikendalikan. Penelitian ini bertujuan untuk mendapatkan model dinamik dari proses kontrol pada kolom distilasi menggunakan MPC serta untuk mendapatkan kinerja yang optimal dari pengontrol MPC. Pengendalian proses dalam kolom distilasi dilakukan dengan mensimulasikan model dinamis kolom distilasi oleh perangkat lunak UNISIM R390.1. Proses optimasi dilakukan dengan penalaan parameter pengontrol MPC seperti waktu sampling ( $T_s = 1-240$  s), prediksi horizon ( $P = 1-400$ ), dan horison kontrol ( $M = 1-400$ ). Perbandingan antara kinerja pengontrol MPC dan PI disajikan dan Kesalahan Integral Absolut (IAE) digunakan sebagai parameter perbandingan. Hasil penelitian menunjukkan bahwa kinerja pengontrol MPC lebih baik dari pengontrol PI untuk perubahan set point 0,95-0,94 pada komposisi produk distilat menggunakan model 1 yang telah dimodifikasi dengan IAE 0,0584 untuk pengontrol MPC dan 0,0782 untuk pengontrol PI.

**Kata kunci:** *model kontrol prediktif, multivariable, penalaan, kolom distilasi*

### INTRODUCTION

The development of more advanced industries has an impact on the increasing demand for energy supplies. Based on Ministry data center energy and mineral resources, the need for energy industry about 33% in 2014 out of a total final energy demand in Indonesia and is projected to continue to grow (DEN RI, 2014). Increasing energy consumption led to the depletion of national energy reserves that are still based on the use of fossil energy such as oil, coal and gas. So there needs to be an intensification process in the industry so that energy consumption is becoming more efficient.

One of the unit operations are most widely used in the petroleum and chemical industry that requires considerable energy supply is a distillation column (Agachi *et al.*, 2006; Liptak, 2007). Separation process using the distillation column in the chemical industry worldwide estimated to be 95% (Enagandula and Riggs, 2006). Not uncommon to the industry did over reflux so that energy is used for the column distillation is usually 30-50% larger than the actual conditions. This is done so that products produced in accordance with the specifications (Riggs, 2000). In addition to the thermodynamic process of distillation it has an efficiency of less than 10% (Agachi *et al.*,

2006). By means of controlling the flow of product composition in distillate and bottom corresponds to the design then the minimization of the use of this energy can be done (Tham, 1999).

To acquire distillation products with high purity very difficult to control if use conventional controller for distillation within having the nature of a column very non linear and due to the strong and natural interaction between loop controlled (Agachi *et al.*, 2006). Composition distillate products can be controlled with reflux, regulating the flow so also composition bottom products can be controlled by arranging enter the heat on reboiler. The reflux flow rate changes could affect the product quality bottom likewise contrarily (Tham, 1999).

Loop control system in distillation known as a multi input multi output (MIMO) or multivariable systems. MIMO systems is more difficult to control than a system with a single input single output (SISO) because of the strong interactions between variables - variable inputs and outputs (Masoumi and Zarandi, 2011).

Model Predictive Control (MPC) is one of the alternative control that was developed to address the control of MIMO system that has interaction loop (Wade, 2004). MPC algorithm has been widely recognized in the industry for its ability to handle the interaction in the process, and the constraint on manipulated variable delay time (Gu and Gupta, 2008). The performance of MPC controller was better than proportional integral (PI) controller on the industry which used distillation column because of its ability in handling the complex effective constraint (Riggs, 2000; Ahmad and Wahid, 2007; Wahid and Ahmad, 2009, 2015; Wahid *et al.*, 2013).

To determine how effective the use of MPC controller in the control of a distillation column, it will be a study of the control of the composition of the distillate product output binary system benzene-toluene, by applying the MPC controller and accompanied with process control tuning parameters such as the sample time ( $T_s$ ), prediction horizon (P), and the control horizon (M), to produce the optimum process control (Camacho and Bordons, 2007). The study was conducted by simulating the dynamic model of the distillation column using UNISIM R390.1. UNISIM R390.1 able to provide a real description as was the case in the actual process. The results of the control of the MPC will then be compared with the results of PI control. The parameters used to compare the

efficacy of both controllers are Integral Absolute Error (IAE), which is calculated from the response graph controlled variable (CV).

## EXPERIMENT

### Software and Model

In the present study, the program used to simulate UNISIM R390.1. R390.1 UNISIM useful for applications in the chemical industry as a chemical industrial design, monitoring capabilities of the existing chemical industry. The process simulator can be used to simulate the process units in steady state and dynamic simulation. In the program UNISIM R390.1 contained unit processes commonly encountered in chemical engineering operations, one of which is a distillation column. In order to perform steady state and dynamic simulation of distillation columns with UNISIM R390.1, it would require some significant parameter of the distillation column so that the simulation can be run smoothly. The parameters that include operating pressure, temperature, type of bait and composition, feed flow rate and others.

The model will be used in the study were stratified distillation column can be seen in Figure 1. The separation of the components is benzene and toluene (binary system).

### Research Variables

There are several research variables. First are Controlled Variables: a variable bonded to be controlled. The studies at this time the dependent variable is the mole fraction of the components in the product and the bottom distillate.

Then, Manipulated Variables: a variable independent of the input variables are used to maintain the controlled variable is at its set point. In this study, the MVs are reflux flow and boil-up flow.

### Variation of Model

Variations performed to obtain more precise models that MPC control can be optimized. Variations of this model done by varying the initial valve opening both reflux and stream flow boil up. It also made changes to the variation increases valve opening at the same initial valve opening. Minimum initial valve opening is determined by trial and error until a stable CV response obtained either distillate CV of composition and composition of bottom.

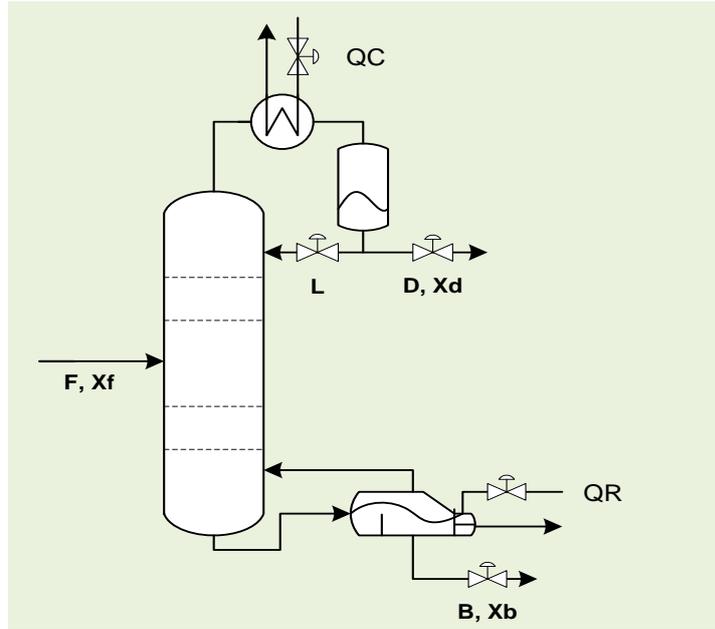


Figure 1. Typical Simple Distillation Column

**Experimental Procedure**

Experimental procedure based on UNISIM R390.1 tutorial and distillation column parameter using exercise sample from Giancoplis (2003).

**Controller Tuning**

MPC controller tuning using non-adaptive DMC tuning strategy (Dougherty and Cooper, 2003). The steps to calculate  $T_s$  (sampling time),  $P$  (prediction horizon) and  $M$  (control horizon) is as follows:

1. Approximate the process dynamics of all controller output to measured process variable pairs with FOPDT models:

$$\frac{y_r(s)}{u_s(s)} = \frac{K_{r_s} e^{-\theta_{r_s} s}}{\tau_{r_s} s + 1} \quad (r = 1, 2, \dots, R; s = 1, 2, \dots, S)$$

2. Select the sample time as close as possible to:

$$T_{r_s} = \text{Max}(0.1\tau_{r_s}, 0.5\theta_{r_s}) \quad (r = 1, 2, \dots, R; s = 1, 2, \dots, S)$$

$$T_s = \text{Min}(T_{r_s})$$

3. Compute the prediction horizon,  $P$ ; and the model horizon,  $N$ :

$$P = N = \text{Max} \left( \frac{5\tau_{r_s}}{T_s} + k_{r_s} \right) \text{ where}$$

$$k_{r_s} = \left( \frac{\theta_{r_s}}{T_s} + 1 \right) \quad (r = 1, 2, \dots, R; s = 1, 2, \dots, S)$$

4. Compute a control horizon,  $M$ :

$$M = \text{Max} \left( \frac{\tau_{r_s}}{T_s} + k_{r_s} \right) \quad (r = 1, 2, \dots, R; s = 1, 2, \dots, S)$$

PI Controller tuning using Ziegler Nichols method for determining Proportional Gain ( $K_c$ ) and Integral Time ( $T_i$ ).

**System Identification**

This study uses a linear empirical model namely FOPDT (first-order plus dead-time). Other models can be nonlinear models as developed by Sjöberg *et al.* (1995) and Abonyi *et al.* (2005). To determine the parameters of FOPDT gain ( $K_p$ ), time constant ( $\tau$ ) and dead-time ( $\theta$ ) using the method II (Luyben, 1996; Marlin, 2000; Seborg *et al.*, 2004).

**RESULTS AND DISCUSSION**

The distillation column has two controlled process variables (PV or CV) and two manipulated variables (MV). Measurable process variables is the composition of output distillate products ( $X_{ID}$ ), which is represented by the output of benzene and bottom product composition ( $X_{IB}$ ) represented by toluene. The two variables were manipulated in the process

of reflux flow rate ( $F_R$ ) and boil-up flow rate ( $F_{BU}$ ). Figure 2 shows the model of a distillation column which is used in the present study.

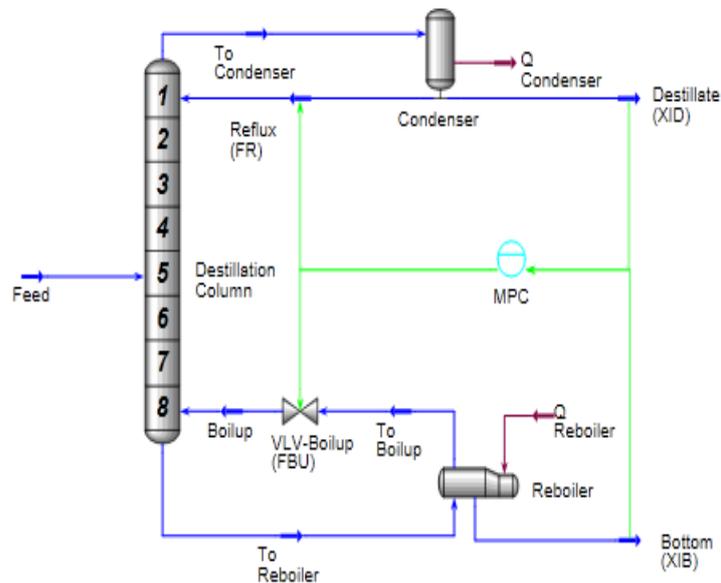


Figure 2. PFD of Distillation in Column with MPC Multivariable Control

Based on Figure 2, reflux flow rate is used to control the composition of benzene in the distillate stream. Meanwhile, boil up flow rate is used to control the composition of toluene in the bottom stream. The alteration of reflux flow rate is controlled by the controller will affect the quality of the product output composition benzene in distillate. Likewise boil-up flow rate alteration will affect the quality of the product composition of output in the bottom toluene.

The alteration of reflux flow rate in addition will affect the quality of the product composition of output in the distillate stream and will also affect the quality of the product composition of output in the stream bottom. Likewise boil-up flow rate alteration in will affect the quality of the composition other than product output in the bottom stream composition and will also affect the quality of the output product in the distillate stream. Thus, any change in flow will be generated reflux 2 PRC and any change in boil up flow charts will be generated 2 anyway, so that will be obtained 4 FOPDTs.

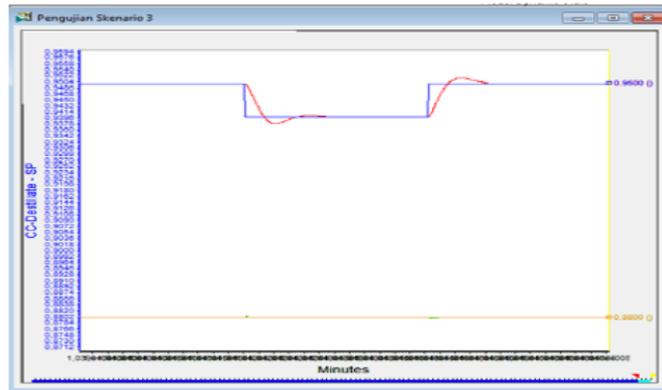
FOPDT models developed by varying the valve opening in from the initial conditions for minimum valve opening until certain openings. Minimum valve opening is the valve opening where the initial conditions on the composition of both benzene and toluene in bottom and

distillate stream in a stable condition or steady. The result showed minimum valve openings for the flow of reflux and boil-up flow was 20% and the optimum model got in that valve opening. The Optimum FOPDT parameters show in Table 1.

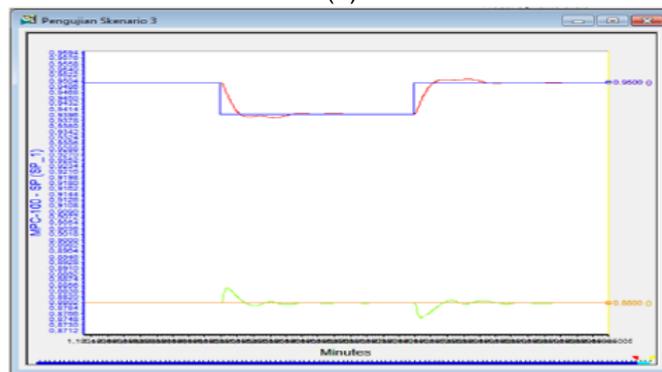
Table 1. FOPDT parameters of Model 1

Model	FOPDT	Kp	$\tau_p$	$\theta$
Model 1	G 1.1	0.3405	36	6
	G 1.2	-0.1081	51	5
	G 2.1	-0.1220	34.5	13.5
	G 2.2	0.12555	13	0

Distillation column control using PI controller performed as a comparison of the performance of MPC controller. Test performance of both PI and MPC controllers made by changing the set point in both composition and in the bottom and distillate streams. The alteration of composition set point in distillate starting from 0.95 to 0.94, then returned to the original point set. The change in the composition distillate set point is called scenario 1. While changes in bottom composition set point starts from 0.90 to 0.89 and return to 0.90. The change in bottom composition set point is called scenario 2. Figure 3 shows the performance of PI and MPC controller at scenario 1, and Figure 4 show the performance of PI and MPC controller at scenario 2.

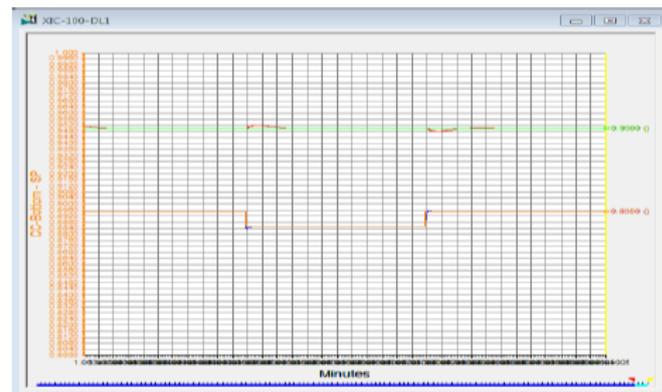


(a)

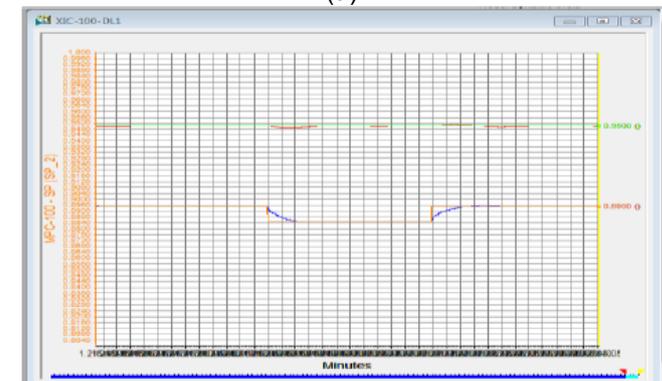


(b)

Figure 3. Performance of PI and MPC controller scenario 1: (a) PI, (b) MPC



(a)



(b)

Figure 4. Performance of PI and MPC controller scenario 2: (a) PI, (b) MPC

Based on calculations, IAE generated by the MPC controller for controlling the composition of benzene in the distillate stream smaller than IAE that generated by the PI controller. This means that the performance of the MPC controller is better than PI for controlling the composition in distillate stream. However, on controlling the composition of toluene in the bottom stream, PI controller is still better than the MPC controller. Table 2 shows IAE calculation both in scenario 1 and 2.

The parameter of controllers were PI controller,

$$\begin{aligned} \text{XIC-Destilate: } K_c &= 5.86, T_i = 10.6 \\ \text{XIC-Bottom: } K_c &= 8.29, T_i = 0.08 \end{aligned}$$

and

$$\text{MPC: } P = 68, M = 1, T = 18, \text{SRL} = 200$$

Table 2. Performance of PI and MPC controller both scenario 1 and 2

Controller	IAE			Deviation
	D	B	Total	
PI	0.0782	0.0092	0.0874	-
MPC Model 1	0.0584	0.0587	0.1171	33.98 %

## CONCLUSIONS

The best dynamic model for controlling the composition of output product from distillation column in binary system (benzene-toluene) and can be applied to multivariable control systems with MPC controller is:

$$\begin{pmatrix} X_{ID} \\ X_{IB} \end{pmatrix} = \begin{pmatrix} \frac{0.3405e^{-6s}}{36s+1} & \frac{-0.1081e^{-5s}}{51s+1} \\ \frac{-0.122e^{-13.5s}}{34.5s+1} & \frac{0.1555}{13s+1} \end{pmatrix} \begin{pmatrix} F_R \\ F_{BU} \end{pmatrix}$$

Non-adaptive tuning strategy DMC cannot be applied to calculate the MPC controller parameter tuning on software UNISIM R390.1.

MPC multivariable controller would work to control the composition of the optimal set point with a narrow range and using a model developed in the range of set point range tested. This can be seen at test set point 0.95 to 0.94 on the distillate product composition using a modified model 1 with IAE 0.0584 for the MPC controller and 0.0782 for PI controllers.

## REFERENCES

- Abonyi, Janos, Janos Madar, Lajos Nagy, Ferenc Szeifert. *Interactive Evolutionary Computation in Identification of Dynamical Systems*. Soft Computing: Methodologies and Applications. *Advances in Soft Computing*. 2005; 32: 73-84
- Agachi, Paul Serban, Zoltán K. Nagy, Mircea Vasile Cristea, Árpád Imre-Lucaci. *Model Based Control: Case Studies in Process Engineering*. German: WILEY-VCH Verlag. 2006.
- Ahmad, A. and Wahid, A. Application of Model Predictive Control (MPC) Tuning Strategy in Multivariable Control of Distillation Column. *Reaktor*. 2007; 11 (2): 66 – 70.
- Camacho, E. F., Bordons, C. *Nonlinear Model Predictive Control: An Introductory Review*. University of Seville, Spain. 2007.
- Dewan Energi Nasional Republik Indonesia. *Outlook Energy Indonesia 2014*.
- Dougherty, D. and Cooper, D. A Practical Multiple Model Adaptive Strategy for Single-Loop MPC. *Control Engineering Practice*. 2003; 11: 141 – 159.
- Enagandula, S., and Riggs, J. B. *Distillation control configuration selection based on product variability prediction*, *Control Engineering Practice*. 2006.
- Geankoplis, Christie John. *Transport Processes And Separation Process Principles 4<sup>th</sup> Edition*. USA: Prentice Hall. 2003.
- Gu, Bingfeng dan Gupta, Yash P. *Control of Nonlinear Processes by Using Linear Model Predictive Control Algorithms*. 2008.
- Liptak, Bella. *Distillation Control and Optimization*. USA: Putman Media. 2007.
- Luyben, William.L. *Process Modeling, Simulation, and Control for Chemical Engineers*. Singapore: McGraw-Hill Inc. 1996.
- Marlin, T. *Process Control: Designing Processes and Control Systems for Dynamic Performance 2nd Edition*. New York: McGraw-Hill. 2000.
- Masoumi, Esmaeil dan Zarandi, Batoul M. Dynamic Simulation and Control of a Distillation Column Using Effective Relative Gain Array. *World Academy of Science, Engineering & Technology*; 2011; 52: 787-792.
- Riggs, James. B. Comparison of Advanced Distillation Control Methods. Texas Tech University. *Final Technical Report April 1994 – March 1999*. 2000.

- Seborg, Dale E., Edgar, Thomas F., dan Duncan A. Malichan. *Process Dynamic and Control*. USA: John Willey and Sons. 2004.
- Sjoberg, J., Zhang, Q., Ljung; L., Benveniste, A., Deylon, B., Glorennec, P., Hjalmarsson, H. and Juditsky, A. Nonlinear Black-box Modeling in System Identification: A Unified Overview, *Automatica*, 1995: 12: 1691 – 1724
- Tham, M. T. *Multivariable Control: An Introduction to Decoupling Control*. University of Newcastle. 1999.
- Wade, Harold L. *Basic and Advance Regulatory Control System Design and Application 2<sup>nd</sup> Edition*. USA: ISA (The Instrumentation, System and Automation Society). 2004.
- Wahid, A dan Ahmad, A. Representative Model Predictive Control. *Proceeding of the 11th International Conference on QiR (Quality in Research)*. 2009.
- Wahid, A. and Ahmad, A. Min-max controller output configuration to improve multi-model predictive control when dealing with disturbance rejection. *International Journal of Technology*. 2015; 6 (3): 504-515
- Wahid, A., A. Ahmad and Vania Cynthia Distillation column control using multiple model predictive control based on representative model predictive control. *Proceeding's The 13<sup>th</sup> International Conference on QiR*. 2013.