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Multivariable Model Predictive Control (4x4) of Methanol-Water Separation in Dimethyl Ether Production

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Abstract. The use of the Model Predictive Control (MPC) controller in DME production from synthesis gas has shown better results than the Proportional-Integral (PI) controller. However, this SISO MPC controller makes the DME production process uneconomical due to the cost of expensive MPC controllers. In this study, a Multivariable Model Predictive Control (MMPC 4x4) controller was designed with four manipulated variables (MV) and four controlled variables (CV). MMPC controllers are proposed to reduce the number of controllers used and overcome inter-variable interactions that affect control performance. The design of the controller includes the identification of inter-variable interactions through first-order plus dead time (FOPDT) empirical modeling and controller adjustments. The four CV's include condenser temperature, output cooler temperature, condenser liquid level, and column liquid level, while the four MV's include condenser duty, cooler duty, distillate product flow rate, and bottom product flow rate. The results show that the interactions between the variables identified include all variables involved, so that a 4x4 matrix containing 16 FOPDT models is obtained. The control parameter values in the form of sampling time (T), prediction horizon (P), and control horizon (M) with optimum control performance are 2, 24, and 10. MMPC control performance is better than MPC, which is shown by IAE decline was 19.92% to 72.86% and ISE reduction was 19.16% to 83.58%.

INTRODUCTION

Dimethyl ether (DME) is the simplest ether group, which consists of two carbon atoms. Dimethyl ether is known to be an alternative energy to be used as a substitute for LPG, gasoline and diesel. DME is a pollution-free, non-toxic fuel, easily degraded naturally, and has a high set of numbers. DME can be produced through dehydration of methanol. The results of the methanol dehydration process are Dimethyl Ether which is still mixed with a little methanol which is not converted, so it needs to be purified. The purification unit consists of 2 steps, including DME purification and methanol purification. The DME purification aims to separate DME from unconverted methanol components. Purification of methanol aims to separate methanol with a little water remaining. The product flow for purification of methanol can be used as a feed back to the process of dehydration of methanol [1-2].

Process of methanol purification from water in DME production has been investigated using a single variable single-input (SISO) model predictive control (MPC) [3] to improve previous control designs which using proportional-integral PI controllers [4]. Technically, SISO MPC has shown better control performance than PI controllers. But economically, the SISO MPC makes the DME production process uneconomical, which is indicated by a negative NPV [3]. This is due to the capital cost of using 4 MPCs greater than 4 PI controllers. This condition can be overcome by using Multivariable MPC (MMPC). MMPC can control processes in a multivariable system so that the entire controlled variable can be controlled using one controller [5-6]. The use of MMPC in controlling the methanol purification process can reduce the number of controllers. Reducing the number of controllers will reduce the capital cost of controller installation.

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In this study, the design of MMPC controllers was carried out for the process of methanol purification from water in the DME production process. This study aims to obtain a process empiric model that has multiple variables on methanol purification and obtains more optimum control performance using MMPC than SISO MPC in methanol purification. The performance of the MMPC controllers designed will be compared to the SISO MPC [3].

METHODOLOGY

The methanol purification process in DME production uses operating conditions based on the DME production plant design by [8]. Methanol purification to regenerate methanol is done using distillation column. MMPC is used to control 4 variables in methanol purification which include condenser temperature, output cooler temperature, condenser liquid level, and column liquid level. Schematic simulation of methanol purification with MMPC is shown in Figure 1. Results of MMPC will be compared with the results of SISO MPC. Problem limitation in this study are as follows:

- Process control design is limited to the methanol purification process.
- Type of controller used is MMPC
- The performance of MMPC will be compared with the SISO MPC that designed by Yanuardi.
- The parameters used in calculating controller performance are Integral Absolute Error (IAE) and Integral Square Error (ISE).

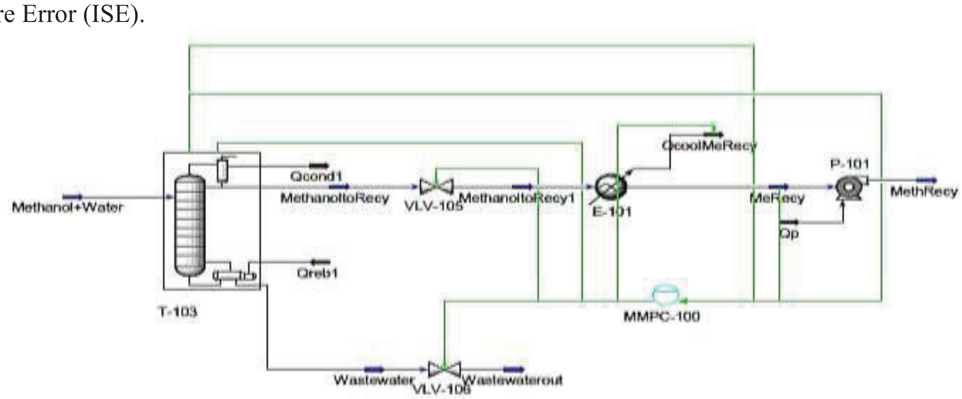

FIGURE 1. Schematic simulation of methanol purification with MMPC

Methanol-Water Separation

Operating condition of distillation column for methanol-water separation shown in Table 1. Feed of the separation process is saturated liquid methanol-water mixture. Feed goes into the distillation column through 19^{th} stage. Overall distillation stage in divided into 2 section, rectifying and stripping. In the stripping section, less volatile component enriched [9]. Whereas in the rectifying section, the volatile component is enriched. The condenser is placed in the reflux system which returns a portion of distillate to the collumn. Reflux flow has a role in increasing the purity of distillate products. Conditions of feed, top, and bottom flow are written in Table 2. The type of controller used in the process is MPC. The list of controlled variable (CV) and manipulated variable (MV) for MMPC is written in Table 3.

TABLE 1. Operating condition of distillation column for methanol-water separation

Parameter	Value
Number of stage (trays)	30
Stage inlet (stage)	19
Condenser pressure (psia)	14.69
Reboiler pressure (psia)	17.17

TABLE 2. Flow specification in methanol-water separation

Variable	Value		
	Feed	Top Product	Bottom Product
Flow rate (kmole/hr)	2375	563.7	2281
Temperature (ºC)	81.74	58.87	104.4
Pressure (psia)	16.04	14.01	17.15
Methanol Fraction (%)	76.28	98.94	0.001
Water Fraction (%)	23.47	0.001	99.98

TABLE 3. List of controlled variable (CV) and manipulated variable (MV)

No.	Controlled Variable	Manipulated Variable
1	Condenser vessel temperature	Condenser duty
2	Output cooler temperature	Cooler duty
3	Condenser liquid level	Flow rate methanol to recy
4	Collumn liquid level	Flow rate waste water

Multivariable (4x4) Models

Interactions between variables in the methanol purification process needs to be indentified to find the behavior of four CV (output) on changes in one MV (input). Thus, if the four MV's are changed separately, there will be 16 process reaction curve (PRC). Each PRC are then modeled empirically using first-order plus dead time (FOPDT) model. The FOPDT transfer function model can be formed in a matrix that describes the interaction between CV and MV in the methanol-water separation process as follows:

$$\begin{bmatrix} CV_1(s) \\ CV_2(s) \\ CV_3(s) \\ CV_4(s) \end{bmatrix} = \begin{bmatrix} G_{11}(s) & G_{12}(s) & G_{13}(s) & G_{14}(s) \\ G_{21}(s) & G_{22}(s) & G_{23}(s) & G_{24}(s) \\ G_{31}(s) & G_{32}(s) & G_{33}(s) & G_{34}(s) \\ G_{41}(s) & G_{42}(s) & G_{43}(s) & G_{44}(s) \end{bmatrix} \begin{bmatrix} MV_1(s) \\ MV_2(s) \\ MV_3(s) \\ MV_4(s) \end{bmatrix} \tag{1}$$

with $G_{11}(s)$ as transfer function of the change of CV_1 to change of MV_1[10]:

$$G_{11}(s) = \frac{CV_1(s)}{MV_1(s)} = \frac{Ke^{-\theta s}}{\tau s + 1} \tag{2}$$

For other functions, it will have the same structure as Eq.2 with the value of FOPDT parameters (K, τ dan θ) according to the PRC obtained. K is the process gain, τ is the time constant, and θ is the dead time.

Multivariable Model Predictive Control Tuning

The value of process parameters in FOPDT modeling can be used to calculate the tuning parameters for MMPC. There are 3 tuning parameters for the MPC system, namely Sampling Time (T), Prediction Horizon (P), and Control Horizon (M) [11]. Sampling time is the time interval used in data retrieval. Prediction horizon is a parameter which shows the range of predictions that will be made when calculating the controller output. Control Horizon is the number of sample intervals needed to achieve steady-state conditions when input is given to the process. Calculation of tuning parameters carried out in this study using the Shridhar-Cooper method [12]. Tuning is also done with Fine Tuning method. Fine tuning is a tuning method by trial and error on MPC tuning parameter values. Tuning is done by changing the value of T, P, M until the optimum results are obtained.

MMPC Performance

The calculation results of the tuning parameters for MMPC input to the process simulation. The tuning parameters are then tested against the condition of the set point change by 5% and the change in feed flow rate by 5%. The performance of the controller will be seen based on 2 types of errors, Integral of Absolute Error (IAE) and Integral of

Square Error (ISE). Error of MMPC is compared with error of MPC designed by [3]. The goal of this study is to get MMPC system which has less error then MPC.

RESULT AND DISCUSSION

Multivariable (4x4) Models

The results of inter-variable modeling in the methanol purification indicate that each variable are interact with each other. Transfer function generated from modeling with FOPDT is 16 equations. Multivariable model in the form of matrix as shown in Eq.3.

$$\begin{bmatrix} CV_1(s) \\ CV_2(s) \\ CV_3(s) \\ CV_4(s) \end{bmatrix} = \begin{bmatrix} \frac{-0.2e^{-0.68s}}{0.15s+1} & \frac{0.008e^{-6.29s}}{2.4s+1} & \frac{-0.001e^{-1.17s}}{0.75s+1} & \frac{-0.0732e^{-0.35s}}{0.15s+1} \\ \frac{-0.012e^{-7.41s}}{1.12s+1} & \frac{-0.502e^{-0.01s}}{0.33s+1} & \frac{0.003e^{-0.05s}}{0.66s+1} & \frac{-0.049e^{-1.21s}}{1.32s+1} \\ \frac{0.584e^{-0.05s}}{0.03s+1} & \frac{-0.004e^{-0.46s}}{0.75s+1} & \frac{(-0.3\text{E}-3)e^{-0.35s}}{0.75s+1} & \frac{-0.007e^{-0.42s}}{1.635s+1} \\ \frac{(0.6\text{E}-3)e^{-0.57s}}{1.32s+1} & \frac{(-0.2\text{E}-3)e^{-10.01s}}{0.27s+1} & \frac{(-6.7\text{E}-5)e^{-0.15s}}{0.27s+1} & \frac{-0.32e^{-0.02s}}{0.76s+1} \end{bmatrix} \begin{bmatrix} MV_1(s) \\ MV_2(s) \\ MV_3(s) \\ MV_4(s) \end{bmatrix} \quad (3)$$

The results of inter-variable modeling show that the K value is very small for directly unpaired variables. This results shows that there is an interaction between CV and MV that is not a pair even though it is not too significant. Eq.3 also shows that there is an interaction between the temperature output of the cooler and the variables in the distillation collumn. It shows that there is influence between the variables of an operating unit and the previous operating unit.

Multivariable Model Predictive Control Tuning

The process parameters in transfer function are used to calculate the tuning parameters with the Shridhar-Cooper method. There is value of the tuning results with Shridhar-Cooper method that cross the maximum value which is prediction horizon (P). The maximum value of prediction horizon is limited to 500. In order to adjust the value of the tuning results, tuning parameters then adjusted using Fine Tuning [13-14]. Value of tuning parameter calculated using Shridhar-Cooper and fine tuning methods are shown in Table 4.

TABLE 4. Tuning parameter by Shridhar-Cooper and Fine Tuning method

Metode Tuning	T	P	M
Shridhar-Cooper	0.025	732.6	348.6
Fine Tuning	2	24	10

MMPC Testing

A. MMPC Testing against SP changes

Comparison of performance between MMPC and SISO MPC controllers in overcoming SP changes is shown in Figure 2 and the error show in Table 5. Overall, MMPC shows a faster response than SISO MPC when there is a change in SP value. In addition, the use of MMPC also reduces errors during SP changes. This is because MMPC uses an interaction model between variables in controlling the process. When there is a change in the SP value on one of the output variables (CV), MMPC will take action for all input variables (MV). The control action carried out aims to overcome the interaction between variables that can make the process controller not optimum.

B. Testing against Disturbance

The comparison of performance between MMPC and SISO MPC in overcoming changes in feed flow rate is shown in Figure 3 and Table 6. Overall, MMPC shows better performance than SISO MPC in overcoming changes in feed flow rate. Variable responses to the use of MMPC show a lower error compared to SISO MPC. The use of MMPC makes the duration of variable deviation caused by increase in flow rate become shorter than the use of SISO MPC. This is because MMPC has the ability to set many input variables (MV) at once by considering the interactions between variables that occur. Setting the input variable value (MV) is done immediately after the occurrence of a disturbance. The value of the input variable (MV) is based on the multivariable process model included in the control algorithm. Multivariable process models are also used to overcome interactions between variables that occur so that process control is more optimum.

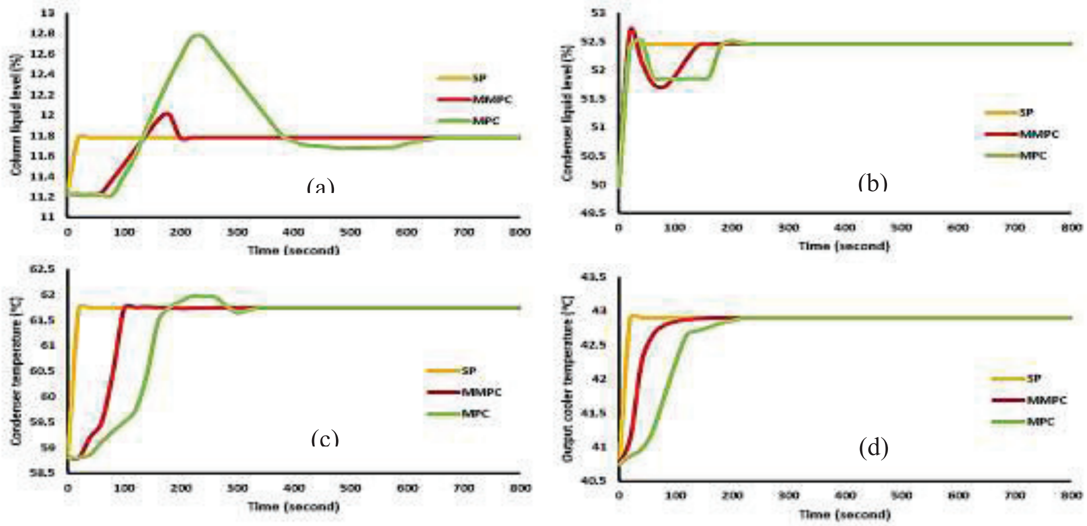

FIGURE 2. Response of control against SP changes in variable (a) column level; (b) condenser level; (c) condenser temperature; (d) temperature output cooler.

TABLE 5. Comparison of the error of MPC and MMPC at 5% set point changes

Variable	IAE		ISE		IAE Reduction(%)	ISE Reduction(%)
	MPC	MMPC	MPC	MMPC		
Column liquid level (%)	211.67	57.44	128.69	24.95	72.86	80.61
Condenser liquid level (%)	75.74	55.93	42.65	30.97	26.15	27.38
Condenser temperature (°C)	352.75	181.22	813.14	434.66	48.63	46.54
Output cooler temperature (°C)	162.10	56.37	248.41	71.05	65.22	71.40

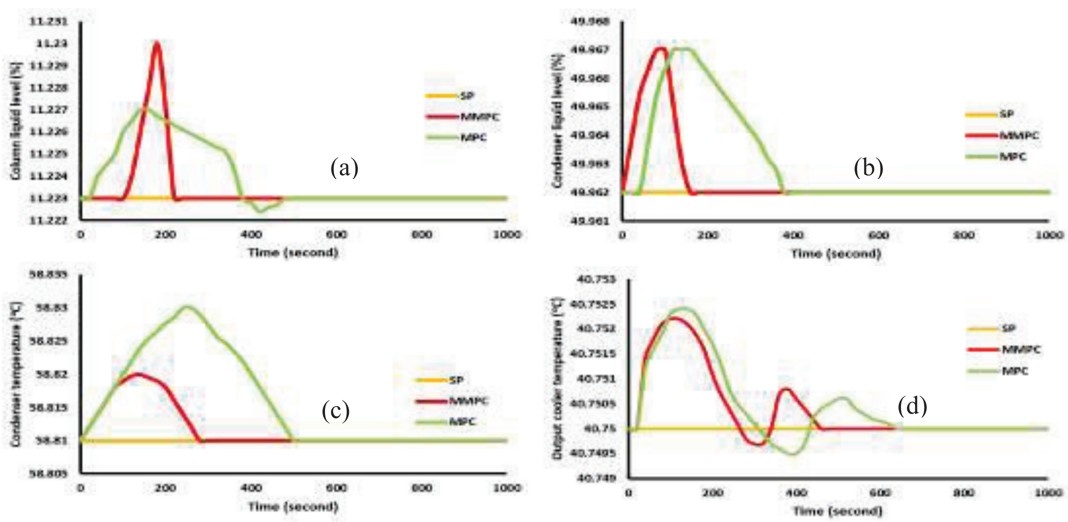

FIGURE 3. Response of control against disturbances in variable (a) column level; (b) condenser level; (c) condenser temperature; (d) temperature output cooler.

TABLE 6. Comparison of the error of MPC and MMPC at increase in flow rate of 5%

Variable	IAE		ISE		IAE	ISE
	MPC	MMPC	MPC	MMPC	Reduction (%)	Reduction(%)
Column liquid level (%)	0.96	0.40	0.003	0.002	58.25	29.04
Condenser liquid level (%)	1.04	0.47	0.004	0.002	55	53.22
Condenser temperature (°C)	5.72	1.75	0.08	0.01	69.50	83.58
Output cooler temperature (°C)	0.53	0.42	0.0008	0.0007	19.92	19.15

CONCLUSION

As a result, each MV (input) interacts with CV (output) forms a multivariable process model in the form of a 4x4 matrix containing 16 empirical equations. The process model can be controlled by Multivariable Model Predictive Control with tuning parameters including T of 2, P of 24, and M of 10. Reduction in IAE by 19.92% to 72.86% and reduction in ISE by 19.16% to 83.58% shows control of MMPC in the process of methanol purification has optimum results compared to SISO MPC and is able to overcome interference due to inter-variable interactions.

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