Model predictive control of vinyl chloride monomer process by Aspen Plus Dynamics and MATLAB/Simulink co-simulation approach

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Abstract. Characteristics of a vinyl chloride monomer (VCM) process is complex and nonlinear due to interactions between units in a reaction-separation network, multiple process streams, and multiple control loops involved. A fluctuation of the thermal cracking unit could result in a difficulty in maintaining downstream units at the setpoints. In this work, an approach to develop a model predictive control (MPC) for the VCM process by deploying a co-simulation between MATLAB/Simulink and Aspen Plus Dynamics is presented. The co-simulation provides more capability and comfortability to design the MPC controller, and evaluate controllability. The VCM process consisting of thermal cracking, quench and distillation is modelled by Aspen Plus Dynamics. The MPC is developed by integrating the concept of plant-wide control and subsystem partitioning. To reduce the burden of mathematical modeling, the MATLAB system identification toolbox is used to develop a multivariable linear model for the MPC controller by reconciling dynamics data from the VCM plant model. Performances of the developed MPC is evaluated under the regulatory test of the EDC feed disturbance. By comparison with the multiple single-input-single-output proportional-integral controllers through the efficiency indexes—an integral squared error, an overshoot and a settling time. Simulation results supported that the MPC controller outperforms proportional-integral controllers.

1. Introduction
A proportional-integral-derivative (PID) controller is generally applied to maintain the set point due to a simple control structure, and ease of implementation. For example, the applications in the pilot reactor in limestone slurry titrated process [1], the ethanol/water distillation column [2], and the integrated distillation column [3]. Groenendijk et al. (2000) and Dimian et al. (2001) studied the plantwide control structures and the dynamic model for the vinyl chloride monomer (VCM) plant with the chlorination reactor, the oxychlorination reactor, and the recycle streams. The study was performed based on the Aspen Dynamic model of a simple VCM process flow diagram. The PID controller technically provides the best performances within small operating regions due to the limitation of the PID controller. Its performance noticeably deteriorates when applying for a large-scale chemical
process that has complex behavior due to reactions, separation network, multiple control loops all related, interactions between the control pairs, and the snowball effect of recycling streams. [4]

Recently, the model predictive control (MPC) is one of the well-established control strategies that provide many advantages, such a capability to handle the non-square system and input-output constraints. Gutierrez et al. (2014) implemented the linear MPC to control activated sludge. Zanin et al. (2002), De Souza et al. (2010), and Popa (2010) applied the MPC control strategy for the fluid catalytic cracking (FCC) process system [5–8]. Fu et al. (2017) presented the MPC controller of the gas fermentation in the bubble-column reactor [9]. From the mentioned literature, the MPCs were implemented in a single reactor/unit that its first-principle or linearized model could be derived. However, the model of the large-scale process is difficult to develop because the nonlinearities of dynamics and interaction of equipment of each unit are involved. An integrated process has multiple input-output variables. More input-output variables could lead to a difficulty to analyze the input-output relationships as well as a selection of MPC tuning parameters.

In this research, we proposed the development of MPC controller for the large-scale process by using plant-wide concept and the subsystem partition to select the essential control pairs representing the dynamics in each subsystem. The plant-wide concept with subsystem partitioning is introduced to identify the sufficient control pairs to stabilize the subsystem. The proper system partitioning could reduce the dynamic complexity as well as the dimension of the state-space model. The co-simulation environment between the Aspen Plus Dynamics (Aspen Technology, Inc.) and MATLAB/Simulink (Mathworks, Inc.) is an efficient tool for testing and evaluating the MPC controller performance with more realistic plant dynamics. Aspen Plus Dynamics is software widely used for studying a process dynamics simulation. It includes varieties of built-in thermodynamic properties and models of equipment such as heat exchangers and reactors. MATLAB is applied for various engineering computations. It is comfortable for programming with various engineering toolboxes available, and it has a capability to connect to the Aspen plus dynamics software. A vinyl chloride monomer (VCM) process is used as a case study. The process consists of the ethylene dichloride (EDC) cracking, quenching, and purification sections, involving complex reactions, gas-liquid equilibrium, and multiple separators. The performance of the MPC controller for the VCM process is verified through a regulatory test and compared to the control performance of the multi-loop PI controllers.

2. Description of a VCM process and a dynamic model

2.1. VCM process description

VCM is produced by thermal cracking of EDC in a cracking furnace. The products of the reaction are VCM and Hydrogen chloride (HCl) gas, while the byproducts are acetylene and ethylene. The reactions are described in equation (1).

\[
\begin{align*}
\text{C}_2\text{H}_4\text{Cl}_2 & \rightarrow \text{C}_2\text{H}_3\text{Cl} + \text{HCl} \\
\text{C}_2\text{H}_2\text{Cl} & \rightarrow \text{C}_2\text{H}_2 + \text{HCl} \\
\text{C}_2\text{H}_4\text{Cl}_2 & \rightarrow \text{C}_2\text{H}_2 + \text{Cl}_2
\end{align*}
\]

(1)

The heat from natural gas combustion is used to adjust the furnace temperature. To prevent the coke formation—a significant problem in the operation of the furnace—, the reaction temperature should maintain below 520 °C. [10] Hot mixed gases from the EDC cracking section pass a series of quenchers and be cooled down by the condensers and recycling liquid streams from other quenchers. After passing a series of the quenchers, the cooled streams of mixed gases and liquids are then purified through two distillation columns. The HCl is top distillate of the first column while the VCM is the top distillate of the second column. At the second column, the VCM product purity is controlled at 0.96 of mole fraction, and the EDC purity at the bottom product is controlled at 0.95 of mole fraction.
2.2. Modeling of VCM process
A steady-state VCM Process is initially simulated in Aspen Plus. The VCM has a highly polar component [11]. Therefore, the thermodynamic property method of RK-ASPN is selected in the model simulation. This property method is an extension of Redlich-Kwong-Soave, and it also applies to polar components.[12] The Aspen Plus model of the VCM process is consequently converted to a dynamic model by Aspen Plus Dynamics. Figure 1 shows a process diagram of the studied VCM process. In EDC cracking section, the fresh EDC feed is preheated by two heat exchangers (HeatX mod) before entering to the north, and south tubes of the cracking furnace which is modeled by two trains of three stirred tank reactors (RCSTR model) in series. The EDC cracking is an endothermic reaction. The heat supplied to the reaction comes from natural gas combustion at the wall of the furnace, which this combustion reaction is modeled by the E04 reactor (Rstoic model). The heat from the flue gas of the natural gas combustion is recovered by the preheaters. The mixed substances of VCM, HCl, and unreacted EDC are cooled down by four quenchers (Flash2 model) in series. The quencher pressure is controlled by the condenser duty. In the purification section, the mixed substances from the E08 quencher were purified by the HCl and VCM distillation columns (RadFrac model). In each distillation column, the column pressure, the top temperature and the bottom temperature are controlled by adjusting the condenser duty, reflux flowrate, and boiler duty.

3. The plant-wide concept with subsystem partitioning and control pair
The VCM process has 19 controlled valves that need to handle. To reduce a large amount of the controlled pairs, the concept of self-optimizing control [13–14] applied to the VCM process with the valve counting method in equation (2).

\[
N_{as} = N_m - N_{o,m} - N_{o,y}
\]
where \(N_{ss}\) is number of steady-state degrees of freedom or number of variables to control, \(N_m\) is the number of manipulated variables which are equal to the number of valves in the system, \(N_{o,m}\) is the number of output variables with no effect the cost (e.g., the liquid level in holdup vessels and columns), and \(N_{o,m}\) is the number of input variables with no effect the cost.

From Figure 1, the number of variables to control (\(N_m\)) for the VCM process is equal to 11 (\(N_m=19\), \(N_{o,m}=0\), and \(N_{o,v}=8\)). The levels of the quenchers, the reflux drums, and the distillation columns are considered as the \(N_{o,v}\) variables. Table 1 shows the input-output pairing for the regulatory layers which the decentralized PI controllers are used for stabilizing the liquid inventories in the process. These selected variables to control will be partitioned into the subsystem in the next step before designing the multivariable MPC controller. Lists of manipulated and controlled variables for the supervisory layer are shown in table 2.

### Table 1. Pairing between manipulated and controlled variables of the regulatory layer for the PI controller.

| Pair no. | Manipulated variable | Controlled variable |
|----------|----------------------|---------------------|
| 1        | Liquid flow rate (V03) | Level of the quencher E05 |
| 2        | Liquid flow rate (V05) | Level of the quencher E06 |
| 3        | Liquid flow rate (V07) | Level of the quencher E07 |
| 4        | Liquid flow rate (V09) | Level of the quencher E08 |
| 5        | Liquid flow rate (V11) | Level of the reflux drum E09 |
| 6        | Liquid flow rate (V14) | Level of the column E09 |
| 7        | Liquid flow rate (V16) | Level of the reflux drum E10 |
| 8        | Liquid flow rate (V19) | Level of the column E10 |

### Table 2. Manipulated and controlled variables of the supervisory layer using for the MPC controller design.

| Manipulated variables                  | Controlled variables              |
|----------------------------------------|-----------------------------------|
| Feed rate of CH\(_4\) and O\(_2\) mixture (V01) | Outlet temperature of the reactor E03 |
| Energy duty Q1 (V02)                   | Pressure of the quencher E05      |
| Energy duty Q2 (V04)                   | Pressure of the quencher E06      |
| Energy duty Q3 (V06)                   | Pressure of the quencher E07      |
| Energy duty Q4 (V08)                   | Pressure of the quencher E08      |
| Condenser duty E09 (V10)               | Pressure of the column E09        |
| Reflux flow rate E09 (V12)             | Temperature at the top column E09 |
| Boiler duty E09 (V13)                  | Temperature at the bottom column E09 |
| Condenser duty E10 (V15)               | Pressure of the column E10        |
| Reflux flow rate E10 (V17)             | Temperature at the top column E10 |
| Boiler duty E10 (V18)                  | Temperature at the bottom column E10 |

In the MPC controller design, a poor control performance could result from the poor selection of the controlled and manipulated variables for predicting the system interactions. Furthermore, the development of the MPC controller for the large-scale process could find a difficulty to solve the large-scale optimization problems and a computational burden time as well. To reduce the complexity of optimization problems, this work proposes the approach of system partitioning for designing the MPC controller of the supervisory layer. The pairing of the subsystem is selected such that the controlled variable is sensitive to a change of the manipulating variable. The state-space model is developed by reconciling dynamics data from the VCM plant model. It is then partitioned into two squared linear systems based on the sensitivity analysis results between output (\(y\)) and input (\(u\)) shown in table 3. The first MPC controller is formulated for handling the cracking furnace and the quenchers, while the second MPC controller is focused on the control of the purification section.
The first MPC controller has five variables to control. The outlet temperature of the EDC cracking furnace affects the EDC cracking rate. The fluctuation in the outlet furnace temperature could lead to a change in the product composition as well. The pressure for each quencher is maintained at a nominal value to stabilize the vapor flow rate in the quench section. The second MPC controller has control for six variables. The pressure of both distillation columns is maintained at nominal values to stabilize the vapor flow rate in the columns. The top and bottom temperature of the distillation column are controlled to achieve the desired compositions. The nominal values and the upper and lower bounds of each manipulated variable are shown in table 4, and table 5 shows the nominal values of the output variables.

### Table 3. The sensitivity analysis between output and input.

| u1 | u2 | u3 | u4 | u5 | u6 | u7 | u8 | u9 | u10 | u11 |
|----|----|----|----|----|----|----|----|----|------|------|
| y1 | 0.03 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| y2 | 19.90 | -4.22 | -8.80 | -1.25 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| y3 | 3.04 | -1.82 | -6.88 | -1.05 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| y4 | 1.01 | -1.04 | -3.91 | -3.28 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| y5 | -6.03 | -0.92 | -2.65 | -1.36 | -4.82 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| y6 | -4.19 | -0.85 | -2.40 | -1.16 | -3.92 | -4.24 | -0.09 | 0.71 | 0.00 | 0.00 |
| y7 | 6.68 | 1.15 | 3.20 | 1.51 | 5.03 | 4.35 | 0.64 | -0.85 | 0.00 | 0.00 |
| y8 | -8.02 | -0.63 | -1.68 | -0.70 | -2.18 | -1.42 | -0.28 | 0.82 | 0.00 | 0.00 |
| y9 | -4.36 | -0.84 | -2.79 | -1.05 | -5.11 | -6.50 | 1.42 | 0.27 | -5.89 | 0.07 |
| y10 | -21.37 | -0.93 | -3.21 | -1.15 | -5.55 | -4.82 | 1.38 | 1.32 | -7.34 | 0.06 |
| y11 | -6.25 | -0.23 | -0.72 | -0.28 | -1.43 | -0.26 | -1.02 | 0.94 | 0.45 | -0.08 |

The lower and upper bounds of manipulated variables (u).

### Table 4. The lower and upper bounds of manipulated variables (u).

| Numbers | Manipulate Variables | Lower bound | Nominal Value | Upper Bound | Unit |
|---------|----------------------|-------------|---------------|-------------|------|
| u1      | Feed rate of CH$_4$ and O$_2$ mixture (V01) | 8500.00 | 9200.00 | 10500.00 | kg/hr |
| u2      | Energy duty Q1 (V02) | -2.10 | -2.02 | -1.95 | Gcal/hr |
| u3      | Energy duty Q2 (V04) | -4.48 | -4.38 | -4.28 | Gcal/hr |
| u4      | Energy duty Q3 (V06) | -1.11 | -1.05 | -1.00 | Gcal/hr |
| u5      | Energy duty Q4 (V08) | -2.07 | -2.00 | -1.93 | Gcal/hr |
| u6      | Condenser duty E09 (V10) | -2.04 | -1.99 | -1.93 | Gcal/hr |
| u7      | Reflux flow rate E09 (V12) | 8200.00 | 10882.61 | 13500.00 | kg/hr |
| u8      | Boiler duty E09 (V13) | 0.59 | 0.65 | 0.69 | Gcal/hr |
| u9      | Condenser duty E10 (V15) | -1.40 | -1.36 | -1.32 | Gcal/hr |
| u10     | Reflux flow rate E10 (V17) | 600.00 | 1602.67 | 5000.00 | kg/hr |
| u11     | Boiler duty E10 (V18) | 1.27 | 1.33 | 1.39 | Gcal/hr |

### Table 5. Nominal value of controlled variable (y).

| Variable | Variable description | Value | Unit |
|----------|----------------------|-------|------|
| y1       | Outlet temperature of the reactor E03 | 504.35 | C |
| y2       | Pressure of the quencher E05 | 13.50 | bar |
| y3       | Pressure of the quencher E06 | 13.20 | bar |
| y4       | Pressure of the quencher E07 | 12.90 | bar |
| y5       | Pressure of the quencher E08 | 12.60 | bar |
| y6       | Pressure of the column E09 | 11.50 | bar |
| y7       | Temperature at the top column E09 | -27.00 | C |
| y8       | Temperature at the bottom column E09 | 75.68 | C |
| y9       | Pressure of the column E10 | 6.00 | bar |
| y10      | Temperature at the top column E10 | 29.35 | C |
| y11      | Temperature at the bottom column E10 | 141.23 | C |
To validate the model quality, the Mean absolute percentage error (MAPE) defined in equation (3) is used as the index

$$MAPE = \frac{100\%}{N} \sum_{t=1}^{N} \left| \frac{y_t - \hat{y}_t}{y_t} \right|$$

(3)

where $y_t$ is the output value from the Aspen Plus Dynamics model, $\hat{y}_t$ is the predicted output value from the state-space model, and $N$ is the number of data point which is equal to 330,000 points for the validation.

The models of the single system model (11x11 input-output variables) and the two-subsystem model (subsystems of 5x5 and 6x6 input-output variables in table 3) are compared with the Aspen Plus Dynamics model of the VCM process under the sequence of input changes from the nominal values shown in table 6 for 330 hours of the simulation time. The comparison index results are shown in table 7. From the results, the two-subsystem model significantly improves the output prediction with less the MAPE index by using the input-output analysis for partitioning the subsystem. The input-output analysis can reduce the unnecessary variables that do not dominantly affect the process dynamics.

Table 6. Input changes applied for the model validation

| Step changes of input from the nominal values |
|----------------------------------------------|
| $u_t$ = \begin{cases} +182.98 \text{ kg/hr} (10 < t \leq 20) \\ -146.89 \text{ kg/hr} (20 < t \leq 30) \end{cases} | $u_t$ = \begin{cases} +0.0556 \text{ Gcal/hr} (40 < t \leq 50) \\ -0.0641 \text{ Gcal/hr} (50 < t \leq 60) \end{cases} | $u_t$ = \begin{cases} +0.0763 \text{ Gcal/hr} (70 < t \leq 80) \\ -0.0826 \text{ Gcal/hr} (80 < t \leq 90) \end{cases} |
| $u_t$ = \begin{cases} +0.0395 \text{ Gcal/hr} (100 < t \leq 110) \\ -0.0462 \text{ Gcal/hr} (110 < t \leq 120) \end{cases} | $u_t$ = \begin{cases} +0.0530 \text{ Gcal/hr} (130 < t \leq 140) \\ -0.5901 \text{ Gcal/hr} (140 < t \leq 150) \end{cases} | $u_t$ = \begin{cases} +0.0306 \text{ Gcal/hr} (160 < t \leq 170) \\ -0.0218 \text{ Gcal/hr} (170 < t \leq 180) \end{cases} |
| $u_t$ = \begin{cases} +316.66 \text{ kg/hr} (190 < t \leq 200) \\ -194.76 \text{ kg/hr} (200 < t \leq 210) \end{cases} | $u_t$ = \begin{cases} +0.0225 \text{ Gcal/hr} (220 < t \leq 230) \\ -0.0297 \text{ Gcal/hr} (230 < t \leq 240) \end{cases} | $u_t$ = \begin{cases} +0.0192 \text{ Gcal/hr} (250 < t \leq 260) \\ -0.0198 \text{ Gcal/hr} (260 < t \leq 270) \end{cases} |
| $u_t$ = \begin{cases} +307.60 \text{ kg/hr} (280 < t \leq 290) \\ -309.31 \text{ kg/hr} (290 < t \leq 300) \end{cases} | $u_t$ = \begin{cases} 0.0108 \text{ Gcal/hr} (310 < t \leq 320) \\ -0.0123 \text{ Gcal/hr} (320 < t \leq 330) \end{cases} |

Table 7. Prediction quality of the output variables

| Variable | % MAPE (x10^2) |
|----------|----------------|
|          | Single system model | Two-subsystem model |
| $y_1$    | 0.03            | 0.01               |
| $y_2$    | 3.02            | 2.13               |
| $y_3$    | 1.40            | 1.50               |
| $y_4$    | 1.63            | 1.63               |
| $y_5$    | 3.79            | 4.10               |
| $y_6$    | 2.20            | 0.19               |
| $y_7$    | 2.79            | 0.22               |
| $y_8$    | 1.58            | 0.10               |
| $y_9$    | 5.68            | 0.73               |
| $y_{10}$ | 7.62            | 1.08               |
| $y_{11}$ | 4.77            | 0.43               |
| **sum**  | **34.50**       | **12.13**          |

4. MPC controller design and evaluation

4.1. MPC design and control structure

MPC is an optimization-based control approach that uses the model to predict and optimize future process responses. In this work, the state-space model describes the operation of the subsystem.
around a nominal operating point. The MPC algorithm is described by the following optimization problem in equation (4).

\[
\min_{\Delta u(k), \Delta u(k+m-1)} \sum_{l=0}^{m-1} \left[ \Gamma_u \left( \| y(k+1|k) - r(k+l) \| \right) \right]^2 + \sum_{l=0}^{m-1} \left[ \Gamma_y \left( \| \Delta u(k+l-1) \| \right) \right]^2
\]

subject to

\[
\dot{x}(k+1) = Ax(k) + Bu(k)
\]

\[
y(k) = Cx(k)
\]

\[
\Delta u = \{ \Delta u | \Delta u_{\text{min}} \leq \Delta u(k) \leq \Delta u_{\text{max}} \}
\]

where \( \Gamma_u, \Gamma_y \) are weighting of each component of input (u) and prediction output (y), respectively. The matrices \( A, B, \) and \( C \) are the state-space matrices of the linear model around a nominal operating point. The MPC predicts the behavior in the future of the process output (y) to minimize error for reference setpoint (r) as a function of the future control moves (\( \Delta u \)). The prediction of y and \( \Delta u \) is determined by the number of prediction horizon (p) and control horizon (m), respectively.

4.2. Co-simulation and implementation of MPC

To perform a closed-loop simulation, co-simulation of the MATLAB/Simulink and the Aspen Plus Dynamics simulator is developed in the Simulink diagram shown in figure 2. The VCM process dynamics are simulated by the Aspen Plus Dynamics simulator, while the control action for each subsystem is computed by the MPC controller block in the MATLAB/Simulink for each interval. The computation of both software is linked through the AMSimulation block (Aspen Technology, Inc.) that is a Simulink block based on COM Automation server (actxserver). It provides a communication link between MATLAB/Simulink and Aspen Plus Dynamics. The integral controller is applied to the control system for eliminating the offsets between the prediction and process outputs.

![Figure 2. Co-simulation approaches between MATLAB/Simulink and Aspen Dynamics.](image)

5. Result performance

The control performance of MPC controller is tested through the regulatory tests of step disturbances in the EDC feed stream by increasing of the +0.5 t/h step disturbance after 5 hours and the -0.8 t/h step disturbance after 20 hours. The performances of the developed MPC controllers are compared with the PI controllers that the parameters are tuned by the IMC tuning method. The MPC tuning parameters are tuned by using the guideline of the prediction and control horizon in [15], and the output weight is set to be the nominal value of each output variable. The tuning parameters of the PI and MPC controller shown in table 8.
The MPC control system is used to compare the performance of the MPC controller with the PI controller. Only the controller performance is shown in figure 3. The results show that the MPC controller has excellent performance compared with the PI controller. The MPC controller has the ISE less than the PI controller. Only the reactor temperature has a maximum absolute overshoot of the MPC controller more than the PI controller. In the first and fourth quenchers, the MPC controller provides good performance compared with the PI controller.

The result of the second MPC controller shown in figure 4. It is clear that the MPC controller has better performance compared with the PI controller. The MPC controller can reject the disturbances while the PI controller can not. The distillation columns have high complexity and nonlinearity.

### Table 8. Tuning parameter of MPC and PI controller

| Parameter                  | MPC             | PI              |
|----------------------------|-----------------|-----------------|
| Control horizon            | 1st MPC         | 2nd MPC         | K, t,             |
| Sampling time              | y1              | 178.88, 9.45    |
| Weighting input            | 0.01            | y2              | 0.24, 1.01        |
| Weighting output           | 0.0135          | y3              | 0.39, 1.19        |
|                           | 0.0027          | y4              | 0.20, 1.39        |
|                           | 504.35          | y5              | 0.20, 1.82        |
|                           | 13.5            | y6              | 0.41, 0.23        |
|                           | 27              | y7              | 177.50, 0.36      |
|                           | 75.68           | y8              | 0.10, 0.49        |
|                           | 6               | y9              | 0.39, 0.13        |
|                           | 29.35           | y10             | 471.00, 0.11      |
|                           | 141.23          | y11             | 0.06, 0.40        |

### Table 9. Index performance in the regulatory tests.

| Settling time of the 1st disturbance (h) | Settling time of the 2nd disturbance (h) | Overshoot of the 1st disturbance | Overshoot of the 2nd disturbance | Integral square error (ISE) x10^3 |
|------------------------------------------|------------------------------------------|---------------------------------|---------------------------------|----------------------------------|
| 1.59                                     | 3.12                                     | -0.25 °C, -0.22 °C              | 0.342 °C, 0.31 °C               | 1.28, 4.84                       |
| 0.62                                     | 5.68                                     | 0.06 bar, 0.17 bar              | -0.08 bar, -0.27 bar            | 0.12, 12.60                      |
| 0.61                                     | 2.43                                     | -0.02 bar, -0.05 bar            | 0.04 bar, 0.08 bar              | 0.01, 0.73                       |
| 0.73                                     | 2.68                                     | -0.02 bar, -0.05 bar            | 0.02 bar, 0.08 bar              | 0.01, 0.02                       |
| 0.74                                     | 4.63                                     | 0.01 bar, 0.08 bar              | 0.02 bar, -0.13 bar             | 0.01, 1.12                       |
| 3.66                                     | 10.79                                    | 0.03 bar, 0.02 bar              | -0.05 bar, -0.03 bar            | 0.01, 0.07                       |
| 2.51                                     | -                                        | 0.02 °C, 0.3 °C                 | -0.03 °C, -0.3 °C               | 0.18, 104.30                     |
| 3.24                                     | 10.38                                    | -0.07 °C, 0.13 °C               | -0.1 °C, 0.21 °C                | 0.06, 6.23                       |
| 8.24                                     | 12.25                                    | 0.02 bar, 0.02 bar              | -0.03 bar, -0.03 bar            | 0.61, 0.06                       |
| 5                                        | -                                        | -0.03 °C, 0.82 °C               | 0.04 °C, 1.1 °C                 | 0.08, 426.50                     |
| 3.7                                      | 10.74                                    | -0.07 °C, -0.15 °C              | 0.1 °C, 0.24 °C                 | 0.19, 9.28                       |
Figure 3. Profiles of the controller actions and output responses under the 1st MPC controller

Figure 4. Profiles of the controller actions and output responses under the 2nd MPC controller

6. Conclusion
In this work, the method to design the MPC controller for a large complex process is presented, and the VCM plant is chosen to study performance controller. The partitioned subsystem is applied to reduce the complexity of the optimization problem, and the plantwide concept is used to select the essential control variable for stabilizing the large-scale process. The linear MPC controller is applied to control a multivariable system by using the state-space subsystem model around the operating point. The co-simulation between MATLAB/Simulink and Aspen Plus Dynamics is applied as a tool for evaluating the proposed MPC performance. From the performance indexes, the results showed that the
MPC controller provides a good performance compared with the PI controller due to an integration of the output model prediction into the calculation of the control action. The improvement in the quality of VCM process modeling by combining the plantwide concept and the partitioned subsystem rises the MPC performance as well. The proposed method provides many advantages in term of technical and industrial aspect. As mentioned previously, a controller design of the large-scale chemical process is a difficult task due to complex reactions, many operating units, and interaction between the process streams. The proposed method is more practical and convenient for the system engineer to take the advantage on the engineering software such Aspen Plus Dynamics and MATLAB/ Simulink for modeling the complex process and evaluating the developed controller system. By applying the concept of the plantwide control and input-output sensitivity analysis, the proper input-output pairs are easy to identify. The proposed concept significantly reduces the complicated task for system identification and the model equation.

References

[1] Alpbaz M, Hapoğlu H, Özkan G, Altuntas S 2006 Application of self-tuning PID control to a reactor of limestone slurry titrated with sulfuric acid. *Chem. Eng. J.* 116 (1) 19

[2] dos Santos Coelho L, Pessôa M W 2011 A tuning strategy for multivariable PI and PID controllers using differential evolution combined with chaotic Zaslavskii map. *Expert Systems with Applications* 38 (11) 13694.

[3] Escobar M, Trierweiler J O 2013 Multivariable PID controller design for chemical processes by frequency response approximation. *Chemical Engineering Science*. 88 1

[4] Luyben W L 1994 Snowball effects in reactor/separator processes with recycle. *Industrial & Engineering Chemistry Research*. 33 (2) 299

[5] De Souza G, Odloak D, Zanin A C 2010 Real time optimization (RTO) with model predictive control (MPC). *Comput. Chem. Eng*. 34 (12) 1999

[6] Lautenschlager M L F, Odloak D 1995. Constrained multivariable control of fluid catalytic cracking converters. *J. Process Control*. 5 (1) 29.

[7] Popa C 2010 Comparison of PI and MPC for control of catalytic cracking process. *Petroleum-Gas University of Ploiesti Bulletin*. 62.

[8] Zanin A C, Tvrzská de Gouvêa M, Odloak D 2002 Integrating real-time optimization into the model predictive controller of the FCC system. *Control Eng. Pract*. 10 (8) 819

[9] Fu Y, Chang L, Henson M A, Liu X G 2017. Dynamic matrix control of a bubble-column reactor for microbial synthesis gas fermentation. *Chem. Eng. Technol*. 40 (4) 727.

[10] Ranzi E, Grottoliti M G, Bussani G, Che S C, Zahng G 1993 A new simulation program predicts EDC furnace performances. *La Chimica e l'industria*. 75 261.

[11] Bezzo F, Bernardi R, Cremonese G, Finco M, Barolo M 2004 Using process simulators for steady-state and dynamic plant analysis: an industrial case study. *Chem. Eng. Res. Des*. 82 (4) 499

[12] Aspen Technology Inc. 2013 Aspen Physical Property Methods. *Aspen Technology Inc.*

[13] Skogestad S 2000 Self-optimizing control: The missing link between steady-state optimization and control. *Comput. Chem. Eng*. 24 (2) 569.

[14] Skogestad S 2004 Control structure design for complete chemical plants. *Comput. Chem. Eng*. 28 (1) 219.

[15] Garriga J L, Soroush M 2010 Model predictive control tuning methods: a review. *Ind. Eng. Chem. Res*. 49 (8) 3505.

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