Representative Model Predictive Control

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ABSTRACT

Some linear model predictive controls (MPCs) are developed to overcome nonlinearities in a distillation column control. Each linear MPC known as a local MPC is a linear model in multi-input multi-output (MIMO) configuration at each certain range of controlled variables (CVs) or output variables from a nonlinear plant. The main problem is how to determine the operating point representing the real condition of the system. Among ten local MPCs have been developed, five local MPCs have small error based on ISE (integral of square error) of the bottom composition ($y_B$) control performance, and three of these as a representative model predictive control (RMPC).

Keywords – linear model, model predictive control, nonlinearity, distillation column, nonlinearity

I. INTRODUCTION

The largest energy consumption in chemical industry is in distillation column. The consumption is about 30 to 50\% and will be reduced until 15\% if using an appropriate control (Riggs, 2000). A conventional control strategy, PI (Proportional-Integral) controller, is so far used in distillation column. Although, the control performance of the conventional controller has satisfied results in distillation column, in a large MIMO configuration, for example in a 4x4 process, the performance control is very poor (Wahid and Ahmad, 2008). Therefore, application of advanced control, such as MPC controller is the best option.

A distillation column has some complicated problems have to be solved. It has two kinds of nonlinearities, dynamic nonlinearity and gain nonlinearity. Dynamic nonlinearity appears because of strong fluctuation in disturbances, while the gain nonlinearity is a consequence of manipulated variable changes. Both nonlinearities have a greater impact in process with high-purity products (Mathur et al., 2008).

Beside nonlinearities, there is a need for high profit in distillation process. This strives for operating the process near constraints to avoid higher operating cost due to operate the process away of constraints. However, the emergence of a region of nonlinearity can disrupt this. Especially if this occurs in the process that requires high-purity product, the Nonlinear MPC (NMPC) becomes the best solution.

NMPC uses a more accurate nonlinear model for process prediction and optimization. Although, the performance control is better than linear MPC, more intensive calculation to produce the control moves by solving large scale nonlinear program on-line at each sampling period is the most serious obstacles (Camacho and Bordons, 2007). This is why its use in industry is less (Qin and Badgwell, 1998; Qin and Badgwell, 2001).

The alternative solution to solve this problem is multi-model MPC or Multiple MPC (MMPC) application (Palma & Magni, 2004). The main problem of MMPC is determining some models that represent the whole operating point of CV (controlled variable) and how to switch one model and another. This paper emphasizes only the first problem. To solve this problem, a system identification strategy will be applied.

System identification is an iterative process, where models are identified by different structures from data and compare model performance. Usually, start from simple model structures to more complexity of the model structure. Note, that higher-order models are not always more accurate. Increasing model complexity increases the uncertainties in parameter estimates and typically requires more data (which is common in the case of nonlinear models).

To identify a liner model, some linear model identification approaches should be used. They are frequency-response models, impulse-response models (using a nonparametric estimate of transient response of dynamic systems, which computes a finite impulse response, FIR, model from the data), low-order transfer functions (process models with first-order plus dead time, FOPDT, second-order plus dead time, SOPDT, or higher-order), input-output polynomial models (ARX, ARMAX, Box-Jenkins, and Output-Error models), and state-space models (using state variables to describe a system by a set of first-order differential or difference equations, rather than by one or more nth-order differential or difference equations).

Usually, to get data we perform some changes in manipulated variables (MVs) and/or disturbances. If we use an MV change, the result model is used in setpoint control. Meanwhile disturbance change is used to get model for

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servo control. But, in this paper we use other way based on the distillation column characteristic that is nonlinearity. Because of the nature, dynamic response of distillation column will be different over different initial condition. From those models we will get representative model predictive control (RMPC).

II. DISTILLATION COLUMN MODEL

There are three model types that are used in this area: empirical, fundamental (that come directly from balance equations, usually called first principle models), and grey box (developed by combining the empirical and fundamental approaches, exploiting the advantages of each type of model) or hybrid (Abdullah et al., 2007).

Skogestad (1997) has developed a distillation model using fundamental model. The schematic diagram of this distillation is depicted in Figure 1. The dynamic model of distillation column uses the following assumptions: Binary mixture; constant pressure; constant relative volatility; equilibrium on all stages; total condenser; constant molar flows; no vapor holdup; linearized liquid dynamics, but effect of vapor flow (“K2”-effect) is included. These assumptions may seem restrictive, but they capture the main effects important for dynamics and control (except for the assumption about constant pressure).

![Figure 1](Typical simple distillation column with LV-configuration (Skogestad, 1997))

There are four output variables in the distillation column, they are the molar fractions of distillate and bottom product ($y_D$ and $y_B$), liquid holdup in condenser and reboiler ($M_D$ and $M_B$). While the input variables are seven variables: $L$ (reflux flow), $V$ (boilup flow), $D$ (distillate product flowrate), $B$ (bottom product flowrate), $F$ (feed rate), $z_F$ (feed composition), and $q_F$ (fraction of liquid in feed). The dynamic response uses the LV-configuration, that is, with reflux $L$ and boilup $V$ are independent variables for composition control and with $D$ and $B$ adjusted to obtain tight level control.

III. EXPERIMENT

Nonlinear dynamic model of distillation column refers to “Column A” model that was developed by Skogestad (1997). The column (as shown by Figure 1) has 40 theoretical stages and separates a binary mixture with relative volatility of 1.5 into products of 99% purity. The Column A model was carried out with MATLAB and SIMULINK environments.

Three problems of distillation control as follows: configuration, temperature control, and composition control. Configuration and temperature control problem are ignored because LV-configuration was selected and there is no temperature control in Column A. So, the problem is how to control the compositions. Because of the use of LV-configuration, the best control will be obtained by one composition control (Skogestad, 1997) and the choice is bottom composition ($y_B$). Therefore, the model configuration is a 2x2 model.

Although, there are two inputs and two outputs in each local model, the need a control of nonlinearity system entails to consider other input variable and the composition in every tray in the local MPC. But, those inputs have no effect to the control variables. This encourages the local MPC is more complex.

The models are stated in state space form (Eq. 1 & Eq. 2).

$$x(k+1) = Ax(k) + Bu(k)$$  \hspace{1cm} (1)

$$y(k) = Cx(k) + Du(k)$$  \hspace{1cm} (2)

To measure the controller performance a series of step change test is performed. Figure 2 shows the step change (setpoint change) of $y_B$ that is used.
IV. RESULTS AND DISCUSSIONS

1. Local model expressions

The equation of Column A in LV-configuration has seven inputs and 82 outputs (41 liquid components and 41 vapor components). The other outputs, two outputs (liquid holdup in condenser, \( M_D \) and in reboiler, \( M_B \) have been controlled by P-controllers, are not involved in local model. The local models of state space forms, therefore, severally consist of matrices \( A \) having 82x82 elements, matrices \( B \) having 82x7 elements, matrices \( C \) having 2x82 elements, and matrices \( D \) having 2x7 elements (as shown by Eq. 3).

\[
A = \begin{bmatrix}
  a_{11} & a_{12} & a_{13} & \cdots & a_{182} \\
  a_{21} & a_{22} & a_{23} & \cdots & a_{282} \\
  a_{31} & a_{32} & a_{33} & \cdots & a_{382} \\
  \vdots & \vdots & \vdots & \ddots & \vdots \\
  a_{81} & a_{82} & a_{83} & \cdots & a_{882}
\end{bmatrix},
\]

\[
B = \begin{bmatrix}
  a_{11} & a_{12} & a_{13} & \cdots & a_{182} \\
  a_{21} & a_{22} & a_{23} & \cdots & a_{282} \\
  a_{31} & a_{32} & a_{33} & \cdots & a_{382} \\
  \vdots & \vdots & \vdots & \ddots & \vdots \\
  a_{71} & a_{72} & a_{73} & \cdots & a_{782}
\end{bmatrix},
\]

\[
C = \begin{bmatrix}
  a_{11} & a_{12} & a_{13} & \cdots & a_{182} \\
  a_{21} & a_{22} & a_{23} & \cdots & a_{282}
\end{bmatrix},
\]

\[
D = \begin{bmatrix}
  a_{11} & a_{12} & a_{13} & \cdots & a_{17} \\
  a_{21} & a_{22} & a_{23} & \cdots & a_{27}
\end{bmatrix}
\]

For matrices \( C \), all of element is 0, except element 1,41 and element 2,1 both is 1. These show that only two outputs will be controlled. Those elements represent distillate composition and bottom composition, respectively. Matrices \( D \) have all elements are 0.

Because of the possible change (\( y_B \) setpoint) from 0.01 to 0.1, there are ten local model MPCs are developed. MPC.01 is a local MPC developed on operating point (initial condition) \( y_D \) is 0.99 and \( y_B \) is 0.01, MPC.02 (initial condition at \( y_D \) is 0.99 and \( y_B \) is 0.01), etc.

2. Representative MPC

We use PI controller to compare with MPC to see the performance control. Skogestad (1997) has been developed the PI controller in the Column A process. We change “Setpoints” block according to Figure 2. Figure 3 shows its performance. ISE of PI tended to rise when its setpoint increased. Even, at setpoint above 0.05 the performance is poor, and tends to unstable above 0.07. However, PI is the best to control \( y_B \) at 0.99 with ISE is only 0.005, meanwhile the ISE to control \( y_B \) is 0.0717.

Figure 4 shows the distillate composition (\( y_D \)) response on the ten operating points (initial conditions) of Column A. The whole response follows the response of the bottom composition (\( y_B \)) as shown by Figure 5. This is very different from the response caused by PI controller. As explained previously, the \( y_D \) response is always in the setpoint (\( y_D = 0.99 \)).

ISE of \( y_D \) is the result of using MPC always far bigger than the ISE of \( y_D \) from the PI. The smallest ISE of \( y_D \) using MPC is 0.0031, achieved by MPC.05 (compare with the ISE’s \( y_D \) use of PI is 0.0005) or six times of that achieved by PI. The least ISE that reached by MPC.05 is also not because its performance is good (in the control of \( y_B \)), but precisely because the performance of \( y_B \) is not good (though not the worst). The result is the smallest because part of the response is due under 0.99, and some others are above it in the balance.

The worst \( y_B \) control performance achieved by MPC.09 with ISE of 0.4041. The worst result of this is the worst of \( y_D \) control performance (ISE = 0.2172), too. While the best performance control of \( y_B \) achieved by MPC.03 (ISE = 0.0015), the next is MPC.02 (ISE = 0.0025), MPC.10 (ISE = 0.0025), MPC.07 (ISE = 0.0047), and MPC.01 (ISE = 0.0135), respectively. MPC.04 has ISE of \( y_B \) is less than PI, but its response is below its setpoint. Beside MPC.04, the
rest MPC (MPC.05, MPC.06, MPC.08, and MPC.09) have responses under their setpoints.
Figure 4 Response of $y_D$ using MPC under some operating points
Figure 5 Response of $y_B$ using MPC under some operating points

Differences in the type of response from the ten local MPC provides a warning to us to be careful in choosing local MPC. Assumption that each local MPC will be the best on the operating point used to build the local MPC is subject to. This is why we must first ensure that local MPC is truly representative of all the operating point where the operating control of a CV is running. That local MPC is called by Representative MPC (RMPC). This RMPC is very important to build a multiple MPC (MMPC). In the Column A control, we propose three RMPCs (MPC.02, MPC.03, and MPC.10) to be used in MMPC.

V. CONCLUSIONS

An important aspect in building a multi-model MPC (MMPC) is to select the local MPC is truly representing the operating points that will be travelled by controlled variable (CV). That local MPC is called by the Representative MPC (RMPC). To get RMPC we have to get the model in each operating point (initial condition), then use it to control the nonlinear system which is the focus. In the case of Column A, we get three RMPC that can be considered as MMPC builders.

REFERENCES


