Inferential Control of Depropanizer Column Using Wave Propagation Model

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Abstract: In the present work a novel inferential control strategy cascaded with a nonlinear profile position controller is employed to control the top and bottom product compositions of a simulated depropanizer column. The inferential model for estimating product compositions is developed using the wave propagation model, and the composition profile position of both rectifying and stripping section is calculated using one temperature measurement from the respective section of the column. It is found that the estimation of the end product compositions using proposed technique may lead to an offset. The accuracy of the proposed inferential model can be further improved by providing an intermittent feedback of composition measurement in the form of an integral action. The wave propagation model of the depropanizer column is used in the Generic Model Control (GMC) architecture to design the profile position controllers.

Keywords: distillation column, nonlinear control, inferential control, profile position observer.

1. INTRODUCTION

A depropanizer column is used to separate propane from a mixture of components ranging from ethane to hexane. It is important to maintain the column product qualities on specification, to limit the negative effects of disturbances and upsets, and to reduce the switching time from one operating condition to another. An effective control strategy is therefore needed to control the depropanizer column. In this work, an inferential model based generic model control strategy is used which can handle disturbances and input uncertainties.

An inferential model is often used in process control when a measurement of the true variable being controlled is not available in real time. Reasons for the lack of real-time measurement include cost, reliability, and long analysis times or long dead times for sensors located far downstream. In these cases, an inferential model provides an estimate of the process variable, which can be used in the design of a controller to provide approximate regulation of the true variable. Tray temperatures are commonly used inferential measurements for product compositions. The temperature control is based on the assumption that the product composition can satisfy its specification when an appropriate tray temperature is kept constant at setpoint. In ideal situation, for a binary distillation column at constant pressure, the temperature at an end of the column is an indicator of the corresponding product composition. However, in case of a multi-component distillation column, tray temperatures do not uniquely determine the product composition. As a result, for these cases it is essential that an on-line analyzer or, at least, periodic laboratory analysis be used to adjust the tray temperature set point to the proper level.

In a Brosilow estimator [Weber and Browsilow (1972), Joseph and Brosilow (1978)] temperatures and flow rates were used for estimating unmeasured disturbances and then the derived disturbance values were used to estimate the product compositions. This estimator is based on a linearized process model. Mejdell and Skogestad (1991a, b) found that the steady state Brosilow estimator was very sensitive to modeling error for the ill-conditioned plant. In the last few decades, the development of composition estimators using partial least squares (PLS) regression have been proposed [Kresta et al. (1994)]. Furthermore, Mejdell and Skogestad dealt mainly with binary distillation columns. For a multicomponent column, tray temperatures do not correspond exactly to the product compositions. Mejdell and Skogestad have shown that the performance of the steady state PLS model for a multicomponent column is worse than that for a binary column. From the results, Mejdell and Skogestad seem to indicate the necessity of a dynamic regression estimator, which was implemented by Kano et al. (2000) in the form of dynamic partial least squares regression.

Gilles et al. (1980) reported the presence of a temperature front within a small area of the column in their extensive experimental study and showed that the locus of the temperature front is related to the product compositions. Gilles and Retzbach (1983) and Marquardt (1988, 1989) characterized the nonlinear behavior of distillation columns by the propagation of concentration profile (C-profile) and temperature profile (T-profile) in the column sections. Lang and Gilles (1990) presented an estimation technique that can be applied to complex processes in chemical industries. Adapting well advanced theories of fixed bed adsorption, Hwang (1991) proposed a nonlinear wave theory for distillation columns which views the movement of composition and temperature profiles as nonlinear waves. They reported that these waves tend to sharpen for most situations and become constant pattern waves. Han and Park (1993) proposed a model based composition controller design incorporating Hwang's nonlinear wave model into the generic model control (GMC) framework of Lee and Sullivan (1988). To overcome the difficulty of composition measurements, Shin et al. (2000) proposed a C-profile position observer based on the temperature measurements. However, their proposed profile position estimation algorithm is applicable only for a binary system. Recently Gupta et al. (2009) has extended the application of profile position control to a debutanizer column.

In this work distillate and bottom propane compositions of a simulated depropanizer column are controlled by using composition to C-profile position cascaded controllers (Figure 1). The compositions are inferred from the C-profile position observer using one temperature measurement from each section (rectifying/ stripping). The objective of this article is to present a new approach to infer and control product compositions using the C-profile position of a depropanizer column, which uses one temperature measurement from the respective (rectifying/stripping) section.

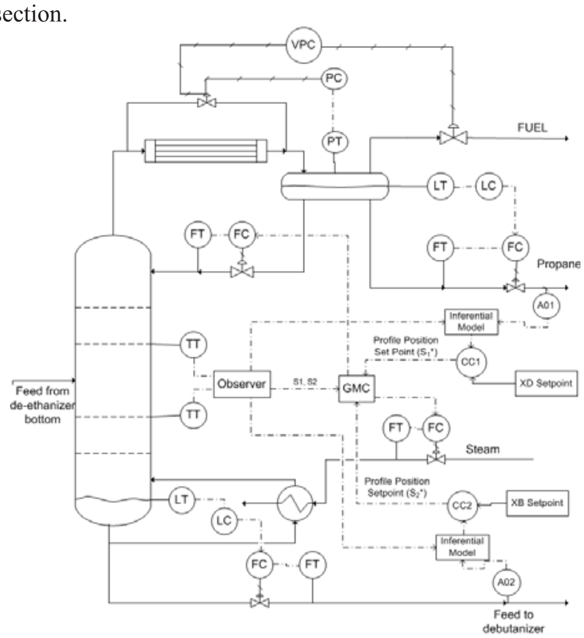

Figure 1: Depropanizer column with control strategy

2. PROCESS DESCRIPTION AND CONTROL STRATEGY

The depropanizer column of a gas recovery unit is simulated in this work [Huang and Riggs (2002)]. The depropanizer column consists of 40 trays, and feed, a mixture of C_2-C_6 components, is fed to the column at 22nd tray (counted from the bottom). The column has a partial condenser and the pressure is controlled via a hot vapor bypass around the overhead condenser. The distillate accumulator level is controlled by adjusting propane product flow rate. In a depropanizer column, the control objective should be to remove impurities (C_4+ components) in the distillate and maintain minimum possible propane loss in the bottom product to maximize the yield of propane in the distillate. This is a separate optimal control problem and is not in the scope of this work. Here the control is achieved by controlling the propane compositions in the distillate and bottom product to their already known optimum targets. The control scheme is shown in Figure 1 and the nominal values required for the distillation column simulation is presented in Table 1. The composition controllers (CC1 & CC2) are PI controllers which generate the profile position setpoints by using the inferred values of propane composition from the inferential model.

reflux rate (k mol/sec)	0.30		
reboiler duty (k joule/sec)	5248.8		
condenser duty (k joule/sec)	-4881.7		
Stream Details			
	feed	*distillate*	*bottoms*
flowrate (k mol/sec)	0.21	0.06	0.15
Temperature (°C)	86	43	112
pressure (k pascal)	3052	1515	1612
Composition (mol %)			
C_2	0.6	2	-
C_3	30	95.1	1.2
C_4	54.2	2.9	76.8
C_5	8.1	-	11.7
C_6	7.1	-	10.3

Table 1: Operating variables for depropanizer column

3. NONLINEAR WAVE MODEL

The dynamic behavior of distillation columns is characterized by the propagation of concentration or temperature profile in the column sections. Numerical simulation results of this typical dynamic behavior for the depropanizer column presented in figure 2 for 10% heavier and 10% lighter feed (Table 2). Propane composition and temperature profile moves up or down to the column ends as a result of increase or decrease of heavier components in the feed. It is also evident from the figure that both the waves ultimately tend to become steep and constant pattern as they move up or down the column.

The travel of such a constant-pattern self-sharpening wave can be characterized by the 'shock wave' velocity [Hwang (1991)] tracking the propagation of specific value of concentration. This wave velocity is derived from the material balance across the wave:

$$u_{\Delta} \equiv \left(\frac{\partial \sigma}{\partial \tau}\right)_{\Delta} = \frac{V}{F} \cdot \frac{\Delta y / \Delta x - L/V}{1 + r\left(\Delta y / \Delta x\right)} \tag{1}$$

where r is vapor to liquid holdup ratio, τ is normalized time ($\tau = tF/NM$), and σ is normalized distance from bottom of the column ($\sigma = k/N$). Assuming the liquid flow is so slow that local equilibrium is attained, y in equation (1) can be substituted with the vapor liquid equilibrium relation. The concentration and temperature waves will travel to either one of the column ends unless the balance of convective transports is carefully maintained to have a zero shock wave velocity with the compositions and flow rates of all streams entering the column sections including feed, reflux, and reboiler vapor flow. Therefore, the behavior of the column is severely nonlinear and sensitive since even a small upset of the balanced condition will lead to a large shift of the composition/temperature profile, giving dramatic changes in the product purity. By analyzing the profile positions for each section and the compositions at the column ends (distillate/bottoms) a model equation can be obtained to correlate the profile position with the compositions from the steady state data for the profile position and the top/bottom compositions collected from the steady state plant model simulation.

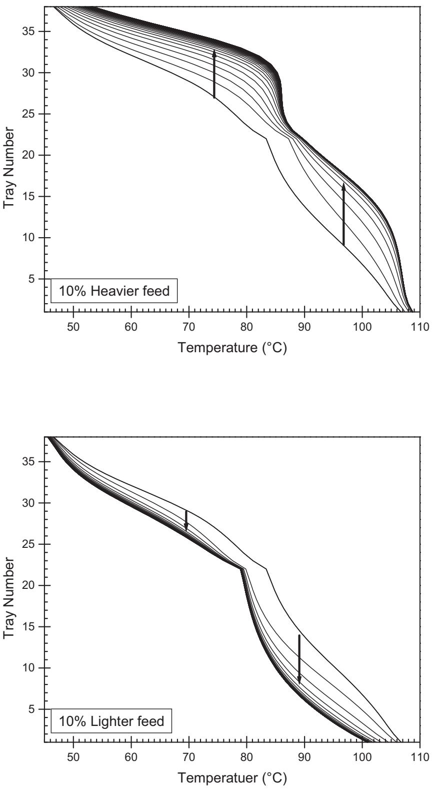

Figure 2: Dynamic profiles of the depropanizer column to a step disturbance (10% heavier feed and 10% lighter feed) of feed composition in open loop (each curve is separated by 5 minutes).

Feed composition

Composition (mol %)	normal	10% lighter	10% heavier	20% heavier	30% heavier
C2	0.6	0.64	0.56	0.52	0.48
C3	30	32.12	27.96	25.99	24.10
C4	54.2	52.51	55.83	57.39	58.90
C5	8.1	7.85	8.34	8.58	8.80
C6	7.1	6.88	7.31	7.52	7.72

Table 2: Feed composition in different scenarios

4. DEPROPANIZER CONTROLLER DESIGN

4.1. Profile position controller

The profile position controller is a nonlinear model-based controller, and is designed by embedding a nonlinear wave model directly into the generic model control (GMC) control framework.

The GMC equation can be written as the following in the case that state vector is a composition profile position S.

$$\frac{dS}{dt} = K_1\left(S^* - S\right) + K_2 \int_0^t \left(S^* - S\right) dt' \tag{2}$$

where, S and S^* are the profile position and its setpoint respectively; dS/dt is the propagation rate of profile. S is expressed in terms of the normalized distance from the bottom of the column ($S = 0$ at the bottom; $S = 1$ at the top). The propagation rate can be expressed from the nonlinear wave model as follows:

$$\frac{dS}{dt} = u = \frac{V}{F}\frac{\Delta y/\Delta x - L/V}{1 + r\left(\Delta y/\Delta x\right)} \tag{3}$$

Distillation columns, in general, have two sections: one is the rectifying section and other is the stripping section. Combining equations (2) and (3) gives one equation for each section as follows:

$$\frac{V}{F}\frac{\Delta y/\Delta x - L/V}{1 + r\left(\Delta y/\Delta x\right)} - K_{11}\left(S_1^* - S_1\right) - K_{12}\int_0^t \left(S_1^* - S_1\right) dt' = 0 \tag{4}$$

$$\frac{\overline{V}}{F}\frac{\overline{\Delta y}/\overline{\Delta x} - \overline{L}/\overline{V}}{1 + r\left(\overline{\Delta y}/\overline{\Delta x}\right)} - K_{21}\left(S_2^* - S_2\right) - K_{22}\int_0^t \left(S_2^* - S_2\right) dt' = 0 \tag{5}$$

where, subscripts 1 and 2 represent rectifying section and stripping section respectively, and L and V are the liquid and vapor flow rates respectively in the rectifying section and $\overline{L}$ and $\overline{V}$ in the stripping section. The profile position and the slope of the equilibrium curve at the representative concentration can be estimated by the profile position observer. Mass balance around the feed tray gives

$$\overline{L} = L + qF \tag{6}$$

$$V = \overline{V} + \left(1 - q\right)F \tag{7}$$

where, q is the liquid mole fraction of the feed. Knowing the feed conditions L, V, $\overline{L}$ and $\overline{V}$ is calculated from equations (4)-(7).

4.2. Online estimation of the profile position

The success of the inferential controller is mainly dependent on the ability to estimate the profile positions for both rectifying and stripping sections. The profile position in each section can be regarded as the location of the constant pattern wave representing a single point corresponding to a representative temperature. The profile position of the constant pattern wave can be determined by tracking the representative temperature instead of the entire wave.

In this case, the profile position observer is designed using the nonlinear wave model for the depropanaizer with an additional feedback of weighted output error of temperature(s) feedback.

$$\dot{S} = \frac{dS}{dt} = \frac{V}{F}\frac{\Delta y/\Delta x - L/V}{1 + r\left(\Delta y/\Delta x\right)} + \sum_{i=l}^{m} k_1\left(T_i\right)\left(T_i - \hat{T}_i\right) \tag{8}$$

$$\frac{\Delta y}{\Delta x} = \frac{\dot{S} + L/F}{V/F - r\dot{S}} \tag{9}$$

$$\hat{T}_i = k_2\left(S_i - S\right) + T_s \tag{10}$$

$$k_1\left(T_i\right) = k_0 \exp\left[-b\left(T_i - T_s\right)^2\right] \tag{11}$$

where, i is the measurement tray number and l and m are the number of first measurement tray and the number of last measurement tray in a column section respectively. For $\Delta y/\Delta x$ and T relationship the steady state plant data can be used which will be associated with the tray efficiencies also. The tray temperature measurement location (26^{th} and 18^{th} tray) in each section is selected based on the inflection points in the temperature waves. The above equations are solved with initial estimates of the profile position S and representative slope $\Delta y/\Delta x$ to obtain the profile position. The sample time for the composition controller has been taken as 2 seconds while that of the profile position controller was 0.2 seconds.

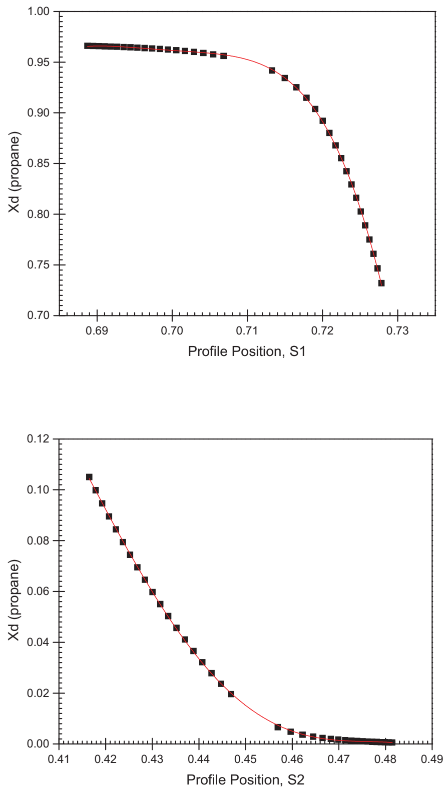

Figure 3: Graphical representation of steady state data set, of rectifying section profile position vs X_D (propane), and stripping section profile position vs X_B (propane).

5. INFERENTIAL CONTROL

In earlier work, the column end compositions were estimated using more than one measurement in the form of temperature, flow rate, and heat duty etc. In the proposed estimator one temperature measurement from each section (rectifying/ stripping) is used to find out the distillate and bottom composition of propane in the depropanizer.

5.1. Model identification using profile position

In this section we are proposing a model based inferential control using the profile position estimation. By analyzing the profile positions for each section and the compositions at the column ends (distillate/bottoms) a model equation can be obtained to correlate the profile position with the compositions. The steady state data for the profile position and the top/bottom compositions collected from the steady state plant model. Figure 3 shows that the data obtained from the plant model can be expressed by a 3rd order polynomial.

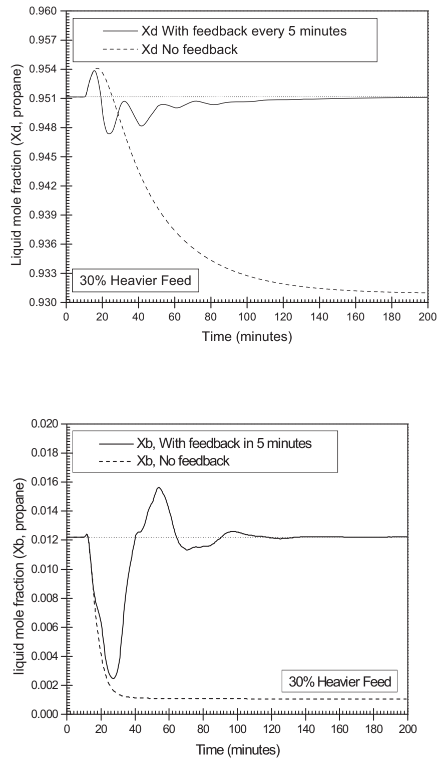

Figure 4: Closed loop transient response of the distillate composition (propane) and bottoms composition (propane) for 30% heavier feed using inferential control, with feedback /no feedback to the inferential composition estimator for the depropanizer column

Figure 4 shows that the proposed model is fair enough to control the end compositions of the depropanizer column. However, the current structure of the model leads to an offset with the final setpoint compositions.

5.2. Model identification using profile position with feedback

Our study leads that the composition measurements are required for the tight control of the end compositions of the depropanizer column. To remove the offset, an integral action as a feedback to the estimator is proposed. The final form of the composition estimator can be expressed as follows:

$$x^{est.} = x^{\text{model}} + k^{'} \int \left(x^{\text{last measurement}} - x^{\text{model}} \right) dt \qquad (8)$$

where, $k^{'}$ is a tuning parameter. Figure 4 shows that the proposed model with feedback is able to control the end compositions of the column without any offset. For the depropanizer column value of tuning parameter $k^{'}$ is tuned at 1 and 0.1 for rectifying section and stripping section respectively, and a lag of 5 minutes allowed for the composition measurement.

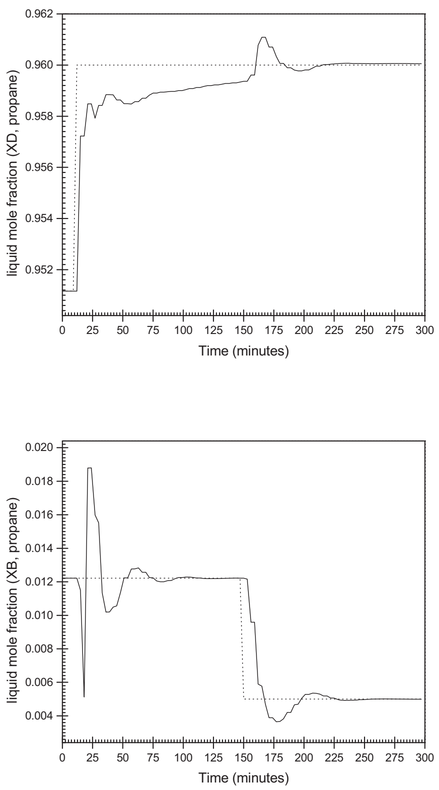

Figure 5: Closed loop transient response for the distillate and bottoms composition (propane) for setpoint change in X_D (propane) of 0.009 (0.951 to 0.96) at 10 minutes followed by a setpoint change in X_B (propane) of 0.007 (0.012 to 0.005) at 150 minutes, with feedback to the inferential composition estimator

6. RESULTS AND DISCUSSION

The depropanizer column with all control loops is simulated to verify the proposed control strategy.

6.1. Effect of composition setpoints change

Two concurrent setpoint changes are implemented to the top and bottom composition controllers. Closed loop transient response for the distillate and bottoms composition (propane) for a setpoint change in X_D (propane) of 0.009 mole fraction (0.95 to 0.96) at 10 minutes followed by a setpoint change in X_B (propane) of 0.007 mole fraction (0.012 to 0.005) at 150 minutes is shown in Figure 5. Increasing the propane purity in the distillate caused an immediate loss in propane content in the bottom causing a shift in the profile position. To maintain the propane composition in the bottom product the GMC controller has to put back the profile position in place which causes a sluggish response in the top composition response after the initial jump. When the bottom composition setpoint is also changed, both the controllers acted speedily because the changes are in favored direction from the viewpoint of the process dynamics.

6.2. Effect of noise and input uncertainty

To examine the robustness aspects of the controller about input uncertainty and temperature measurement noise, a simulation experiment is conducted on the depropanizer controlled by the proposed control strategy. During the simulation experiment following setpoint changes and disturbances are given to the system:

Setpoint change in X_D (propane) at 10 minutes (from 0.95 to 0.96).

Setpoint change in X_B (propane) at 150 minutes (from 0.012 to 0.01).

Step disturbance in the feed composition at 300 minutes (20% heavier feed, Table 2).

The following uncertainties have been taken into account during the simulation experiment:

Random disturbance in the feed flowrate (±5%)

Random disturbance in the reboiler heat duty (±10%) and reflux rate (±10%)

Temperature measurement noise (±0.5 °C)

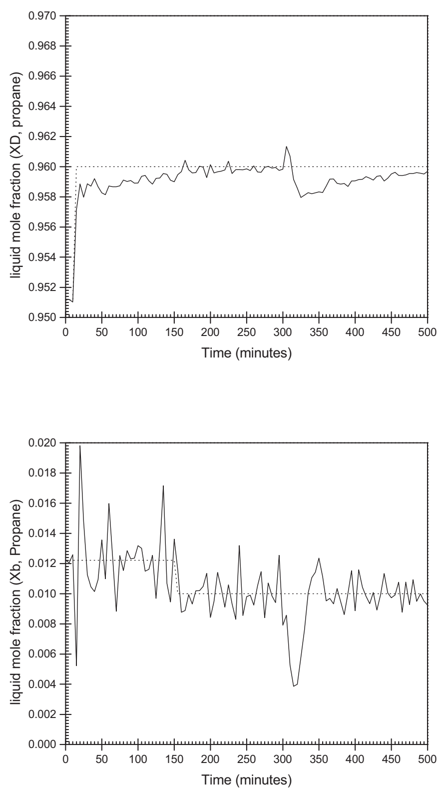

Figure 6: Effect of noise and input uncertainty: closed loop transient response in X_D (propane) and X_B (propane)

The distillate and bottom propane composition responses are shown in Figure 6. In spite of the severe input disturbances and measurement noise, the proposed controller is able to control the product propane compositions with reasonable speed of response and accuracy.

7. CONCLUSIONS

This study has shown a method of developing an inferential model for process control of depropanizer column using the observed profile position. A nonlinear profile position observer has also been developed to estimate the profile position of the column section with sufficient accuracy using temperature measurement. The profile position has been shown to be a powerful approach to building such models and uses the existing available measurements in the depropanizer. However, steady state plant data is needed for design of such models which may be collected while the process is operating under a feedback structure. Under a process/model mismatch, cascaded inferred composition to nonlinear profile position controller performed adequately well in controlling the depropanizer column. It will be interesting to compare the performance of the proposed controller with other nonlinear controller using input-output linearization controller or nonlinear model predictive controller which are much more computationally intensive than the proposed controller.

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