Inferential Active Disturbance Rejection Control of a Distillation Column

Fahad Al Kalbani, Jie Zhang

School of Chemical Engineering and Advanced Materials, Newcastle University, Newcastle upon Tyne NE1 7RU, UK (Tel: +44-2087240; e-mails: f.k.s.al-kalbani@newcastle.ac.uk; jie.zhang@newcastle.ac.uk)

Abstract: Distillation columns are the major energy consumers in petrochemical and chemical industry and their efficient operation is essential for energy saving and product quality enhancement. This paper presents an inferential active disturbance rejection control (ADRC) method for product composition control in distillation columns. The proposed control strategy integrates ADRC with inferential feedback control. Tray temperatures are used to estimate the top and bottom product compositions which are difficult to measure on-line without time delay. In order to overcome the colinearity in the tray temperature data, principal component regression (PCR) is used to build the soft sensors, which are then integrated with ADRC. In order to overcome static control offsets caused by the discrepancy between soft sensor estimations and the true compositions, intermittent mean updating is used to correct PCR model predictions. The proposed technique is applied to a simulated methanol-water separation column.

Keywords: distillation columns, composition control, inferential control, active disturbance rejection control, principal component regression.

1. INTRODUCTION

Distillation is the most commonly used separation method at various industrial scales with more than 40,000 columns in operation worldwide (Kiss, 2014). Distillation can generate more than 50% of both capital and plant operating costs in a typical chemical plant which can have a significant impact on overall plant profitability (Kiss and Bildea, 2011). A suitable integration of distillation columns with the total process leads to substantial energy savings but the scope for this is usually limited (Smith and Linnhoff, 1988). Distillation columns are the major energy consumers in petrochemical and chemical industry. Most distillation columns' operations require a high amount of energy and still remain very energy inefficient; they account for more than 40% of the amount of energy utilized in the refining and bulk chemical processes. Moreover, many columns are subject to significant interaction among the control loops and have operational constraints which complicate their dynamic behavior, making them more difficult to control and optimize. Furthermore, composition analyzers usually possess long time delay which deteriorates the achievable control performance. As a result, advanced control techniques are required to minimize the energy consumption and to meet the product composition specifications. In the control of distillation columns, the main important task is to avoid column drift by stabilizing the column profile (Ling and Luyben, 2009).

In order to address these issues in distillation column control, this paper presents an inferential active disturbance rejection control (ADRC) method which integrates ADRC with inferential control. ADRC has been shown to give better control performance than PID control, but most of the reported applications of ADRC are in the area of motion control (Gao et al., 2001). Inferential estimation can overcome the impact of the long time delay in composition measurements on distillation product composition control performance. To the authors' knowledge, the integration of ADRC and inferential control has not been reported in the literature.

The paper is organised as follows: Section 2 gives an overview of active disturbance rejection control and inferential control. An integrated ADRC and inferential control strategy for distillation columns is presented in Section 3. Section 4 presents the development of soft-sensors for distillation product composition using principal component regression (PCR). Section 5 presents the control performance of the proposed control strategy. The last section draws some concluding remarks.

2. AN OVERVIEW OF ADRC AND INFERENTIAL CONTROL

Uncertainties commonly exist in many practical systems. Thus, dealing with uncertainties is a fundamental problem in control system design. Significant efforts have already been made and much progress has been achieved to overcome and solve this issue. Two sources of uncertainties are the internal parameters or sometimes called the un-modelled dynamics uncertainties and external disturbance uncertainties. To address these, many control techniques, like adaptive techniques, disturbance observers or estimators, and robust control techniques, have been developed. Moreover, various approaches with the idea of estimating external disturbances are introduced, such as the unknown input disturbance observer based control (Gibson, Kolmanovsky, and Hrovat, 2006), disturbance accommodation control (Kim, 2013) and many others. These techniques usually require a mathematical model of the controlled plant. It can be noticed that the modern control paradigm has an over dependency on the mathematical models. This makes many of the modern control methods not very practical because they need a mathematical model for the physical plant which sometimes is not realistic to attempt in the real world especially for complex nonlinear systems (Chen, Zheng, and Gao, 2007). ADRC breaks this barrier because it is after the PID control algorithm and it does not depend on the model accuracy of the plant. The ADRC method has been developed as a practical control method and proven as a powerful tool to deal with such mixed uncertainties. ADRC directly estimates and compensates the total disturbances using extended state observer (ESO) leading to uncertainties reduction ability (Han, 2009; Gao, 2003). The second main advantage is that ADRC has few tuning parameters and it requires very little knowledge of the controlled dynamic system.

2.1 The structure of ADRC

Fig. 1 shows the structure of ADRC, which consists of three main components: transient profile generator, nonlinear weighted sum, and extended state observer.

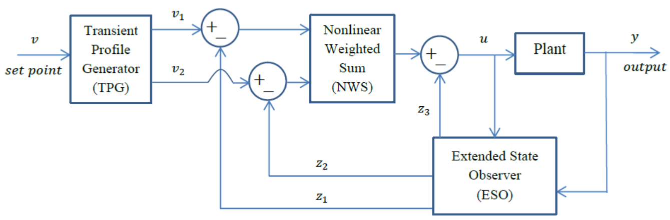

Fig. 1. Structure of ADRC

A.Transient Profile Generator

To overcome the impact of sudden set point jumps, Han (2009) mentioned the necessity of constructing a transient profile generator (TPG) which smoothes out sudden setpoint changes. When there is a sudden unexpected change of the setpoint, the output signal of the plant will track the TPG output and will change gradually to reach the desired setpoint. TPG is represented by Eq(1).

$$\begin{cases} \dot{V}_1 = V_2 \\ \dot{V}_2 = -r.sign\,(V_1 - V + \frac{v_2|v_2|}{2r}) \\ \dot{V}_2 = fhan\,(v_1 - v(t), v_2, r, h_0) \end{cases} \tag{1}$$

In Eq(1), V represents the control target, V_1 is the desired trajectory, V_2 is the derivative of the desired trajectory and *fhan* represents the Han function. The speed of transient profile can be slowed down or speeded up by selecting a suitable value of r which is sometimes called tracking speed. The value of r can be selected depending on the physical limitation of the controlled plant.

B. Nonlinear Weighted Sum

The linear weighted sum is another limitation of the conventional PID controller which considers only the present, predictive and accumulative errors. Han (2009) presents an alternative nonlinear function that depends on the error signal magnitude to generate the control signal. For example using the following nonlinear feedback to determine the control action u:

$$u = |e|^{\alpha}\, sign\,(e) \tag{2}$$

The control error signal, e, can reach zero much rapidly in finite time with $\alpha < 1$.

C. Extended State Observer

ESO is the first observer which is independent of the mathematical model and is introduced in the context of ADRC (Yi et al., 2014). The main idea of ESO is to estimate on-line the variables which are often inaccessible instrumentation wise, such as model errors, external disturbances and internal nonlinear dynamics of the physical plant, and to effectively compensate for the unexpected disturbances. ADRC can successfully drive the controlled process output signal to the desired target if ESO has an accurate estimation for the external disturbances, model error and internal nonlinear dynamics of the plant and to effectively compensate for the unexpected disturbances in control effort. ESO can enhance the adaptability of the control strategy (Xia et al., 2007).

Consider the following 2nd order system (Han, 2009):

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = f(x_1, x_2, d_e, t) + bu \\ y = x_1 \end{cases} \tag{3}$$

where y is the controlled output, u is the manipulated variable, and $f(x_1,x_2,d_e,t)$ represents a multivariable function of the states, the external disturbance and time. This multivariable function corresponds to the total disturbance $d_t(t)$. Using the total disturbance $d_t(t)$ as an additional state variable, Eq(3) can be modified as follows:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = x_3 + bu \\ \dot{x}_3 = d_t(t) \\ y = x_1 \end{cases} \tag{4}$$

The three states $x_1(t)$, $x_2(t)$, and $x_3(t)$ can then be estimated by an ESO and the estimated states are denoted as $z_1(t)$, $z_2(t)$, and $z_3(t)$ respectively. Upon observation of Fig. 1 and to eliminate the effect of the total disturbance, the control law of the ADRC strategy can be written as:

$$u = \frac{g - z_3(t)}{b_0} \tag{5}$$

where g is the desired closed loop dynamics, $z_3(t)$ is the estimate of the total disturbance $d_t(t)$, and b_0 is a rough approximation of the parameter b in Eq(3).

2.2 Inferential control

Composition analyzers are typically utilized to measure product compositions in distillation columns. Many composition analyzers like gas chromatography commonly have substantial time delays. The other drawback is that the reliability of composition analyzers is usually quit low. Thus, utilizing this type of analysers in distillation column composition control will consequently involve high maintenance cost. As a result, the achievable composition control performance is reduced significantly (Shinskey, 1979). In these cases, an estimate of the difficult-to-measure controlled variable should be acquired from an inferential model. Inferential control is commonly done by measuring secondary process variables which are then used in estimating the primary controlled variables (Kano et al., 2000). It can be supreme to conventional PID feedback control especially for processes which has long dead times and high order. It circumvents several of the issues associated with composition analyzers. The control scheme introduced by Shiren et al. (1997) utilizes the easily available tray temperatures to estimate the product compositions and uses the estimated compositions in feedback control. In a binary distillation column, the top product composition can be controlled by controlling the top tray temperature and the bottom product composition can be controlled by controlling the bottom tray temperature because the temperature measurements are more economic, more reliable and almost without any time delay. It is mentioned by Joseph (1999) that the tray temperatures have strong correlation with the product compositions. Kister (1990) mentions that tray temperatures are commonly utilized in distillation composition control unless the difference between the boiling points is small. However, a single tray temperature may not give good representation of product composition. Joseph and Brosilow (1978) developed techniques for constructing optimal and sup-optimal estimators and compared these two approaches for inferential control of product composition in a simulated multi-component distillation column. Alataiqi and Abdel Jabbar (1997) introduced an inferential feed-forward control algorithm for a petroleum fractionator with indeterminate blends of hydrocarbons as the feed. Unspecified and unmeasured disturbances of feed composition are estimated from secondary measurements and the manipulated variables are changed to keep the product quality at its desired level. Multiple linear regression (MLR) is usually not suitable for building inferential estimation models for distillation columns due to the colinearity among tray temperatures. Instead, PCR or partial least squares (PLS) regression should be utilized due to the following reasons (Kasper et al., 1992):

- The strong correlations among the measurements of tray temperatures;
- PCR and PLS are capable of providing a robust solution in the case of correlated or collinear input variables, where MLR encounters the ill-conditioned issue.

Mejdell and Skojested (1991) presented PCR estimator to estimate the distillation columns product composition from flow rate measurements and secondary temperature measurements. PCR is applied to tackle the strong collinearity among the temperature measurements. Zhang (2001) reports that inferential feedback control of distillation compositions can be implemented by using PLS and PCR models. Zhang (2006) presents a new method for removing the static estimation and control off-sets using intermittent mean updating technique.

3. INTEGRATED ADRC AND INFERENTIAL CONTROL

The proposed inferential ADRC scheme for distillation column product composition control is shown in Fig. 2. In the considered distillation column, the primary controlled variables are top composition (y_1) and bottom composition (y_2), secondary measurements (x) are the tray temperatures and the disturbances are feed flow rate and feed compositions. Product composition control is done by measuring secondary variables, tray temperatures, which are used to estimate the controlled variables through soft sensors. PCR models are built to estimate the top and bottom product compositions from tray temperature measurements. Alternatively, PLS models can also be used. The static estimation and control off-sets due to the operating condition variations and model inaccuracy are eliminated via intermittent mean updating introduced by Zhang (2006).

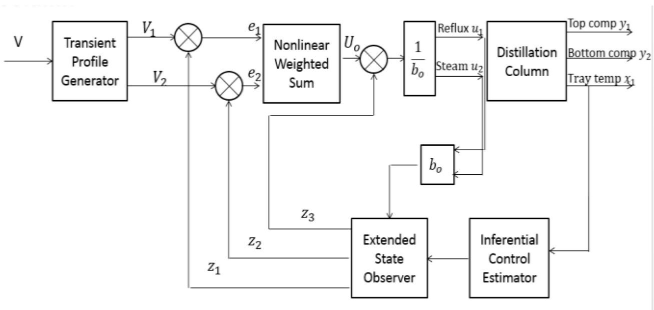

Fig. 2. ADRC scheme integrated with the inferential control

4. PCR MODEL BASED SOFTWARE SENSORS

The distillation column considered in this paper is a comprehensive nonlinear simulation of a methanol-water separation column which has 10 trays. A nonlinear tray by tray mechanistic model has been developed utilizing mass and energy balances. The following assumptions are used: negligible vapour holdup, constant liquid holdup and perfect mixing in each stage. The simulated column is based on the Wood and Berry's column at University of Alberta in Canada. The nominal operation data for this specific column are given in Table 1. The nominal operating point considered in this study is the top composition at 93% and the bottom composition at 7%. To generate data for building PCR inferential estimation models, series of random disturbances were added. Fig. 3 shows the top and bottom product compositions in the generated data. Fig. 4 shows the corresponding tray temperature data. It can be seen that correlation exists among tray temperature measurements.

Table 1. Nominal distillation column operation data

Variables	Nominal values
Top composition (y_1)	93% (wt) methanol
Bottom composition (y_2)	7% (wt) methanol
Reflux flow rate (u_1)	10.108 g/s
Steam flow rate (u_2)	13.814 g/s
Feed composition (d_1)	50.12% (wt) methanol
Feed flow rate (d_2)	18.23 g/s

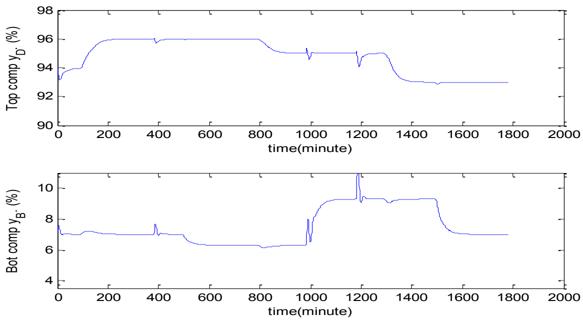

Fig. 3. Top and Bottom product compositions

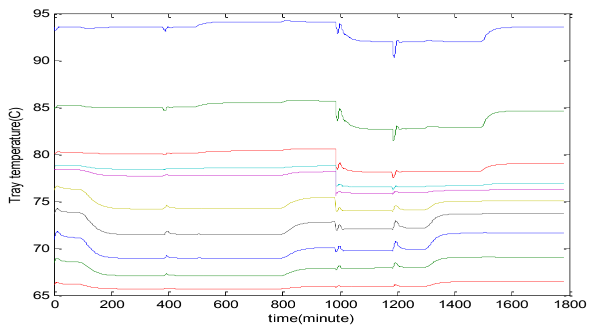

Fig. 4. Tray temperatures

The inferential model links the compositions at time t with tray temperatures at time t. The model can be defined in the following form:

$$y(t) = \theta_1 T_1(t) + \theta_2 T_2(t) + \cdots + \theta_{10} T_{10}(t) \qquad (6)$$

where y represents the product compositions, T_1 to T_{10} represent the tray temperatures from tray 1 to tray 10 respectively, θ_1 to θ_{10} are model parameters corresponding to tray temperatures, and t indicates the discrete time. The data are scaled to zero mean and unit variance before model building. The data is divided into training data set (samples 1 to 1189) and the testing data set (samples 1190 to 1982). PCR models with different numbers of principal components were developed on the training data and tested on the testing data. The PCR model with the lowest error on the testing data is considered as having the appropriate number of principal components.

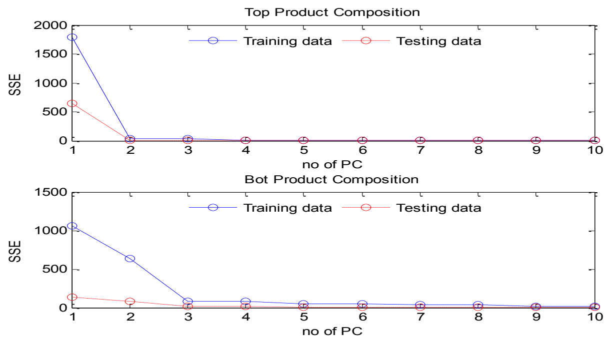

Fig. 5. SSE of different PCR models

Fig. 5 shows the sum of squared errors (SSE) of several PCR models on the training and testing data. It has been seen that the PCR model with 4 principal components offers the best performance for the top composition on the testing data and 9 principal components give the best performance for the bottom compositions on the testing data. As a result, 4 principal components are used in the top composition model and 9 principal components are used in the bottom composition model. The developed PCR models for top and bottom product compositions are as follows:

$$y_D = 93 + 0.04500\Delta T_1 - 0.03572\Delta T_2 - 0.130424\Delta T_3 + 0.189102\Delta T_4 - 0.034529\Delta T_5 + 0.08806\ \Delta T_6 - 0.31151\Delta T_7 - 0.32551\Delta T_8 - 0.0666\Delta T_9 - 0.67369\Delta T_{10} \qquad (7)$$

$$y_B = 7 - 0.39444\Delta \mathrm{T}_1 + 0.071845\Delta T_2 - 0.22059\Delta \mathrm{T}_3 + 1.356745\Delta T_4 + 0.21753\Delta T_5 + 0.88404\Delta T_6 - 0.98501\Delta T_7 - 0.87577\Delta T_8 - 1.75977\Delta T_9 - 0.71489\Delta T_{10} \qquad (8)$$

where y_D and y_B are top and bottom compositions (wt%) respectively, and ΔT is the deviation of a tray temperature from its nominal mean values.

Fig. 6 shows the PCR model predictions. It can be seen from Fig. 6 that the model predictions are very accurate, especially for the top product composition. However, some prediction offsets are visible for the bottom product compositin. Table 2 gives the SSE for top and bottom product compositions of the PCR models.

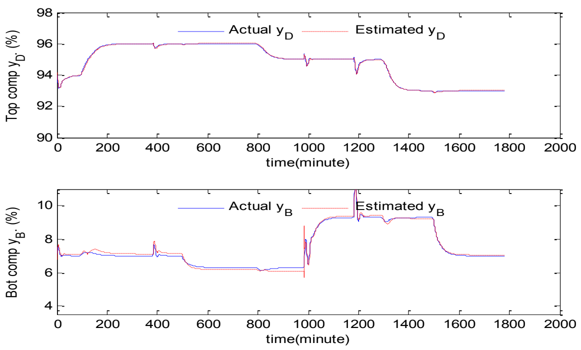

Fig. 6. Predictions from the PCR model

5. INFERENTIAL FEEDBACK CONTROL

In the composition control studied here, the manipulated variables for the top and bottom product compositions are reflux flow rate (*L*) and steam flow rate (*V*) to the reboiler respectively. The tray temperatures are fed to the PCR software sensor and the estimated compositions are utilized in feedback control as shown in Fig. 7. The feedback controller is designed as an ADRC controller. The considered disturbances are feed rate and feed composition disturbances.

To study the performance of the control scheme, the following disturbances were added to the simulated column. The feed rate was increased by 15% at the 1200th minutes, the feed composition was increased by 15% at the 600th minutes. Furthermore, series setpoints changes are applied to both top and bottom product compositions.

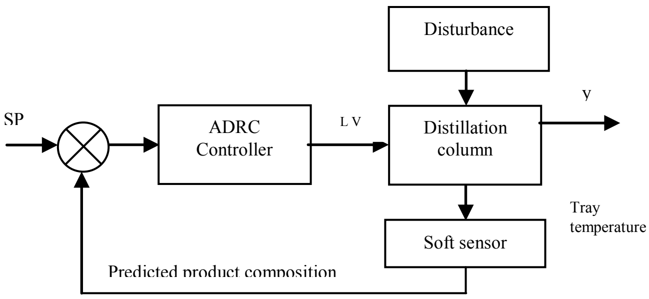

Fig. 7. Inferential feedback control of product composition

The inferential ADRC control schemes are compared with tray temperature control. Through investigating and analysing the data presented in Fig. 3 and Fig. 4, it was found that temperature of the 8th tray (from the bottom column) has the largest correlation coefficient with the top product composition and the temperature of the 2nd tray has the largest correlation coefficient with the bottom product composition. Thus, temperatures of 2nd and 8th trays were controlled to indirectly control the bottom and top product compositions respectively. Temperatures at 2nd and 8th trays corresponding to top composition of 93% and bottom composition of 7% are 85.9° C and 70.5° C respectively. Hence, the setpoint for tray 2 and 8 temperatures were set at 85.9° C and 70.5° C respectively. Temperature setpoints corresponding to other product compositions were identified from simulated process operation data. Multi-loop PI controllers were used to control both tray temperatures.

Fig. 8 shows the control performance of tray temperature control. It can be seen from Fig. 8 that tray temperature control has large offsets in product compositions when the process operating condition changes. This is due to the fact that the relationship between a product composition and a single tray temperature can be substantially affected by process operating condition variations such as the presence of disturbances and changes of setpoints.

Fig. 9 shows setpoint tracking and disturbance rejection performance of inferential ADRC across a wide range of setpoint changes, feed composition and feed rate disturbances. The setpoint was smoothed by TPG. It can be seen that the top product composition is well controlled with negligible static control offsets, but large static control errors exist for the bottom product composition after process operating condition changes. This static control error is due to the PCR model errors, which can get large when operating condition changes, e.g. setpoint and/or disturbance changes.

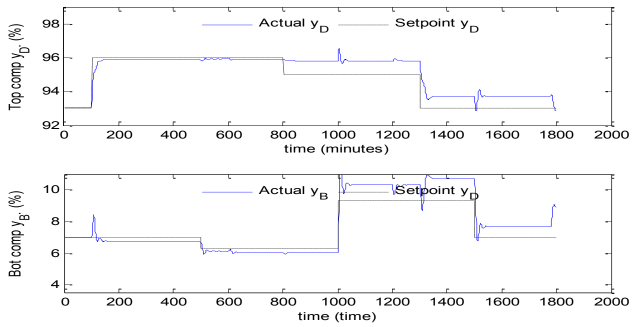

Fig. 8. Control performance of tray temperature control

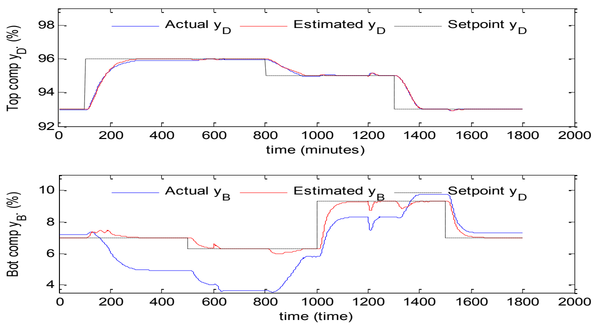

Fig. 9. Responses of actual and estimated product compositions (without mean updating)

To overcome the static control offset problem due to the changes in process operating conditions, the intermittent process variable mean updating strategy proposed by Zhang (2006) is used here. When a new steady state is reached, the static values of tray temperatures and product compositions are used to replace the mean values of these variables in the PCR models. It should be noticed here that only occasional product composition measurements are required. Fig. 9 shows the control performance with mean updating. It can be shown from Fig. 9 that, by using the mean updating technique, the static control offsets are eliminated.

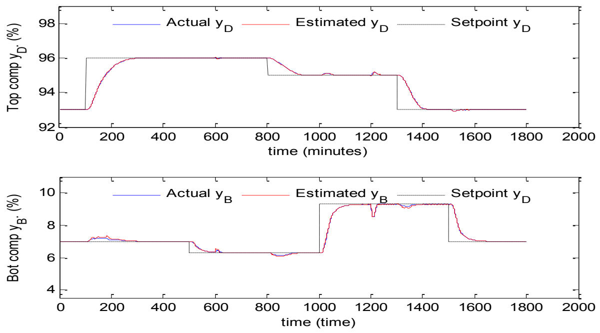

Fig. 10. Responses of actual and estimated product compositions (with mean updating)

6. CONCLUSIONS

An inferential ADRC control method is proposed for distillation column composition control. Inferential estimation models for product compositions are developed from process operational data using PCR. The estimated product compositions are then used in an ADRC controller. Intermittent mean updating of process variables is used to eliminate static model estimation offsets due to variation in process operating conditions and the associated static control offsets. The proposed control method is applied to a simulated methanol-water separation column. Simulation results indicate the effectiveness and success of the proposed inferential ADRC control method. As a future work the inferential ADRC control method will be applied to high purity distillation columns and heat integrated distillation columns.

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