Multivariable Inferential Feedback Control of Distillation Compositions Using Dynamic Principal Component Regression Models

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Abstract

Multivariable inferential feedback control of distillation compositions using principal component regression (PCR) models is presented in this paper. Both static and dynamic models are studied. PCR model based software sensors are developed from process operational data, so that the top and bottom product compositions can be estimated from multi-tray temperature measurements. The problems of co-linearity in tray temperature measurements are addressed by using PCR. Static estimation bias and the resulting static control off-sets are eliminated through mean updating of process measurements. Application to a simulated methanol-water distillation column demonstrates the advantage of dynamic PCR model based inferential feedback control. It is shown that dynamic PCR model based inferential estimations are more robust to process operating condition variations than those based on a static PCR model.

Keywords: Software sensors, inferential control, principal component regression, distillation column control.

1. Introduction

There are many processes in chemical industry where the primary variables to be controlled are difficult to measure or cannot be measured fast enough. For example, in the control of product compositions in distillation columns composition analysers such as gas chrotomography usually possess significant time lags typically between 10 to 20 minutes (Mejdell and Skogestad, 1991). In such cases, effective control of product composition cannot be achieved by direct feedback control based on the much delayed composition measurements. To address this problem, inferential control can be used (Brosilow and Joseph, 1978; Guilandoust *et al.*, 1988; Budman *et al.*, 1992; Lee and Morari, 1992). In inferential control, the difficult to measure controlled variables are estimated from some easy to measure process variables and then used in feedback control.

The primary variables to be controlled in a distillation column are the top and bottom product compositions. Composition analysers possess quite long time delays and, furthermore, they are usually expensive and difficult to maintain. Therefore, in distillation composition control, it is a usual practice to use certain tray temperatures to represent product compositions and control these tray temperatures. However, using a single tray temperature to represent product composition has some drawbacks (Mejdell and Skogestad, 1991), such as the relationship between tray temperature and product composition depends on the feed composition and the product composition at the other end of the column and column pressure variations can affect tray temperatures. To overcome these problems, multiple tray temperatures should be utilised. Due to the strong correlation among tray temperature measurements, multiple linear regression using the ordinary least square method is usually inappropriate and the principal component regression (PCR) or partial least squares (PLS) methods should be utilised (Kaspar and Ray, 1992; Kresta *et al.*, 1991). Zhang (2001) reported using PCR and PLS models in the inferential feedback control of distillation compositions and presented a technique for eliminating static estimation and control off-sets through mean updating. The PCR and PLS models consider in (Zhang, 2001) are of static form. In this paper, it is shown that inferential estimation and control performance can be improved by using dynamic PCR models. It is shown that a dynamic PCR model is more robust to process operating condition variations than a static PCR model.

This paper is presented in four sections. Section 2 presents static and dynamic PCR model based software sensors. Section 3 presents inferential feedback control of distillation compositions based on these software sensors. Finally, Section 4 contains some conclusions of this study.

2. PCR model based software sensor

The distillation column studied in this paper is a comprehensive nonlinear simulation of a methanol-water separation column. A nonlinear tray by tray dynamic model has been developed using mass and energy balances. This simulation has been validated against pilot plant tests and is well known for its use in control system performance studies (Tham *et al.*, 1991a; 1991b). The following assumptions are imposed: negligible vapour holdup, perfect mixing in each stage and constant liquid holdup. The nominal operation data for this column are listed in Table 1.

In this study the nominal operating point considered is the top composition at 95% and the bottom composition at 5%. To generate data for building PCR and PLS inferential estimation models, random perturbations of ±15% were added to the feed rate and the feed composition. Measurement noises of the distribution N(0°C, 0.1°C) were added to the tray temperature measurements. Figure 1 shows the top and bottom product compositions while Figure 2 shows the tray temperatures. The sampling time used is 1 minute. It can be seen from Figure 2 that the tray temperatures are highly correlated.

Table 1. Nominal distillation column operation data

No. of stages	10
Feed tray	5
Feed composition	50 % methanol
Feed flow rate	18.23 g/s
Top composition	95 % methanol
Bottom Composition	5 % methanol
Top product rate	9.13 g/s
Bottom product rate	9.1 g/s
Reflux rate	10.0 g/s
Steam rate	13.8 g/s

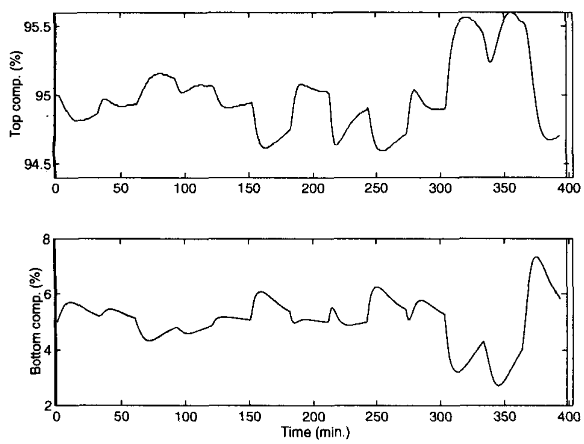


Figure 1. Top and bottom product compositions

2.1 Building static PCR model

The static model here refers to the model where the compositions at time t are estimated from tray temperatures at time t only. The model is of the form:

$$y(t) = \theta_1 T_1(t) + \theta_2 T_2(t) + \ldots + \theta_{10} T_{10}(t) \qquad (1)$$

where y represents the product compositions, T_1 to T_{10} represent, respectively, the temperatures of trays 1 to 10, θ_1 to θ_{10} are model parameters, and t is the discrete time.

The data were scaled to zero mean and unit variance and the reason for this is to allow data with different ranges to be used within the same model. Next, data is divided into a training data set (samples 1 to 200) and a testing data set (samples 201 to 390). PCR models with different principal components were developed on the training data and tested on the testing data. The number of principal components retained in the model is determined based on the minimum sum of squared errors (SSE) on the testing data.

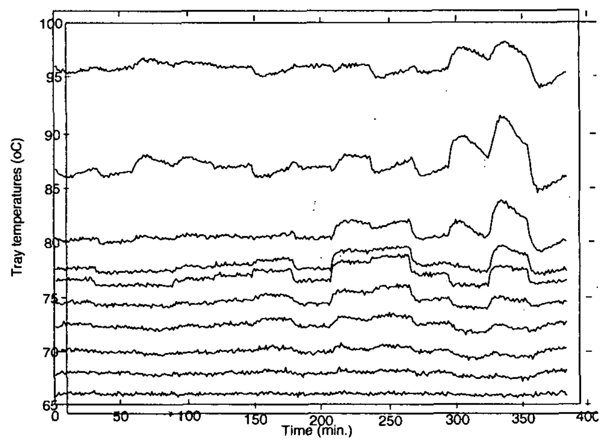


Figure 2. Tray temperatures

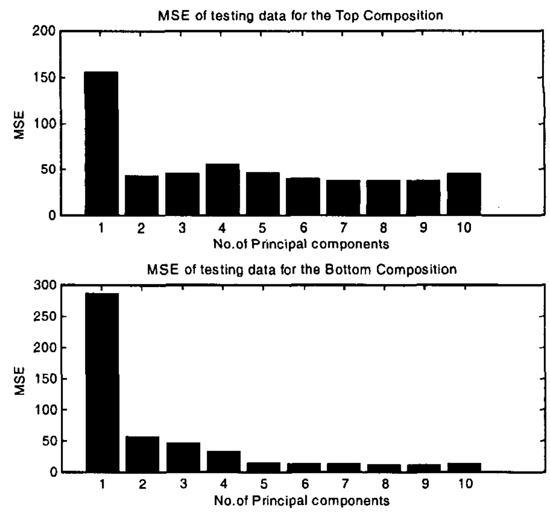


Figure 3. SSE on testing data for PCR static models

Figure 3 shows the SSE of PCR static models with different numbers of principal components on the testing data. It can be seen that 7 principal components give the best performance for the top composition and 9 principal components give the best performance for the bottom composition. Thus the appropriate numbers of principal components for the top and bottom composition models were determined as 7 and 9 respectively, which give, respectively, the SSE on the testing data as 36.5321 and 11.2941. These SSE values are based on the scaled data.

2.2 Building dynamic PCR models

The inferential estimation accuracy could be further improved if a dynamic PCR model is developed. Here first order, second order, and third order dynamic PCR models were developed. As an example, the first order dynamic PCR model is of the following form:

$$y(t) = \theta_{1,1}T_1(t) + \theta_{1,2}T_1(t\text{-}1) + \theta_{2,1}T_2(t) + \theta_{2,2}T_2(t\text{-}1) + \ldots + \theta_{10,1}T_{10}(t) + \theta_{10,2}T_{10}(t\text{-}1) \quad (2)$$

Data scaling and data partition is the same as in developing the static PCR model. The appropriate numbers of principal components were once again determined by the least SSE on the testing data. Table 2 shows the numbers of principal components and the SSE on the testing data of these dynamic PCR models. Once again the SSE values are based on the scaled data.

Table 2. Number of principal components and SSE of different dynamic PCR models

Model orders		SSE	No. of principal components
1	Top comp.	4.7626	13
	Bottom comp.	1.0965	18
2	Top comp.	3.5377	16
	Bottom comp.	0.8340	23
3	Top comp.	3.0147	13
	Bottom comp.	0.8663	37

It can be seen that the dynamic PCR models quite significantly improve the estimation accuracy over the static PCR model, especially the second order and third order models. The differences between the second order and third order models are not significant. Thus the second order dynamic PCR model can be used.

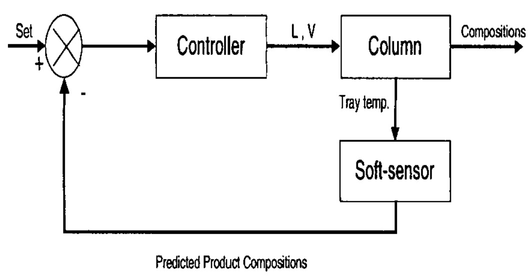


Figure 4. Inferential feedback control structure

3. Inferential feedback control of distillation compositions based on PCR models

The software sensor based inferential feedback control structure is shown in Figure 4. The reflux rate (L) and steam flowrate to the reboiler (V) are the manipulated variables for composition control. The tray temperatures are fed to the PCR software sensor and the estimated compositions are used in feedback control. The feedback controller can be of any form such as a multi-loop controller or a multivariable controller. In this study, a multi-loop PI controller was used.

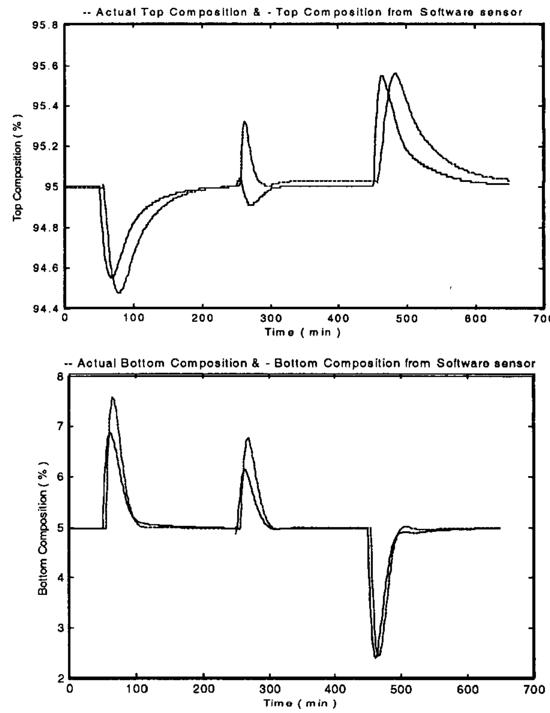


Figure 5. Responses under the static PCR model based controller

Four inferential feedback control schemes with the four software sensors (static and the first to the third order dynamic PCR models) were developed. For the purpose of comparison, a tray temperature based distillation composition controller and a composition analyser based composition controller were also developed. In the tray temperature based composition control, a single tray temperature was used to represent the product composition. Through analysing the data shown in Figures 1 and 2, it was found that temperature of the 8^{th} tray (from the column bottom) has the largest correlation coefficient (-0.91) with the top product composition while temperature of the 2^{nd} tray has the largest correlation coefficient (-0.93) with the bottom product composition. Therefore, temperatures of the 2^{nd} and the 8^{th} trays were controlled to indirectly control top and bottom product compositions respectively. At the nominal operating point (top composition at 95% and bottom composition at 5%), temperatures at the 2^{nd} and the 8^{th} trays are 86.6°C and 70°C respectively. Therefore, the setpoints for tray 2 and 8 temperatures were set as 86.6°C and 70°C respectively. In the composition analyser based composition control, a 5 min measurement lag was assumed. For all the cases, multi-loop PI controllers were used and tuned using the BLT tuning method (Luyben, 1986).

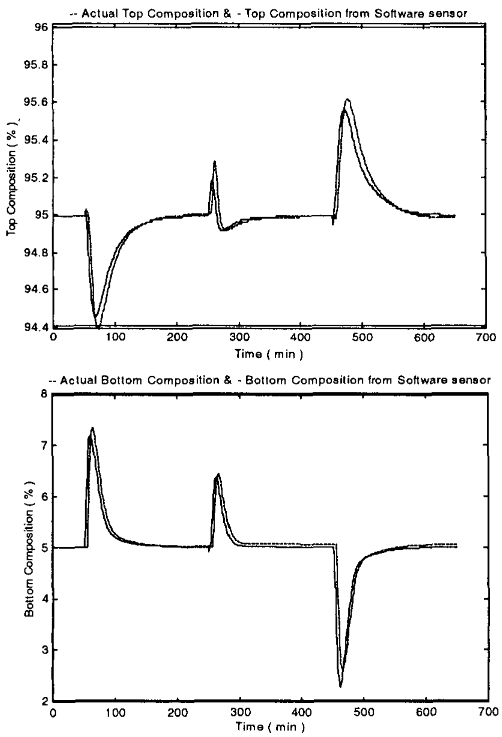


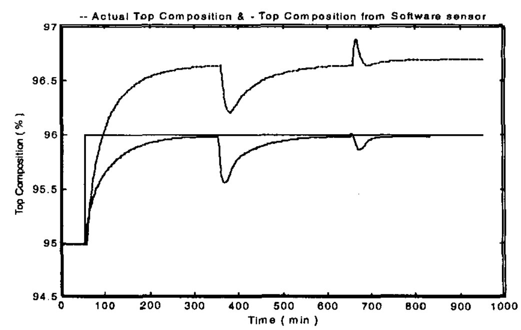
Figure 6. Responses under the 2^{nd} order dynamic PCR model based controller

Table 3. SSE of different control schemes

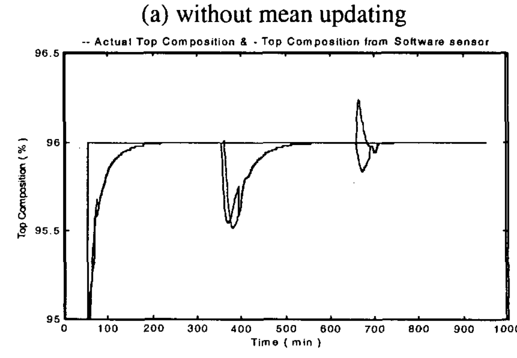
Control schemes	SSE in Top Comp.	SSE in Bottom Comp.
static PCR model	23.1681	274.8978
1^{st} order dynamic PCR model	22.1829	223.1171
2^{nd} order dynamic PCR model	21.8111	221.7452
3^{rd} order dynamic PCR model	21.3367	220.9866
Tray temperature control	25.1967	373.9638
Composition analyser control	35.8802	661.7613

To study the performance of these control schemes, the following disturbances were added to the simulated column. The feed rate was increased by 15% at the 51^{st} minutes, the feed composition was increased by 15% at the 251^{st} minutes, the feed rate was decreased by 15% at the 451^{st} minutes, and finally the feed composition was decreased by 15% at the 651^{st} minutes. Table 3 shows the SSE of different control schemes for the above sequence of disturbances. It can be seen from Table 3 that all the PCR software sensors based inferential control schemes gave better performance than temperature control and composition analyser based control. Among the inferential feedback control schemes, the dynamic PCR model based schemes give better performance than the static PCR model based scheme, particular the 2^{nd} and 3^{rd} order dynamic PCR model based schemes.

Figures 5 and 6 show, respectively, the responses of the static PCR model and the 2^{nd} order dynamic PCR model based schemes under the above sequence of disturbances. In these figures, the dashed lines represent the actual "measured" responses of compositions and the solid lines represent the corresponding model predictions. Note that there is a 5 min time delay in the actual composition responses. It can be seen that the 2^{nd} order dynamic PCR model gives more accurate estimations that the static model. The static estimation errors and the related static control off-sets from the 2^{nd} order dynamic PCR model are smaller than those from the static model, especially in the top product composition.

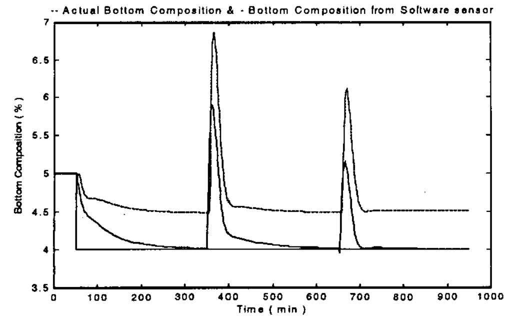


(a) without mean updating

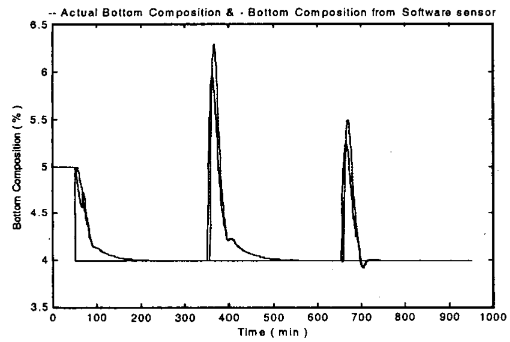


(b) with mean updating

Figure 7. Responses of top composition of the static PCR model based inferential feedback controller

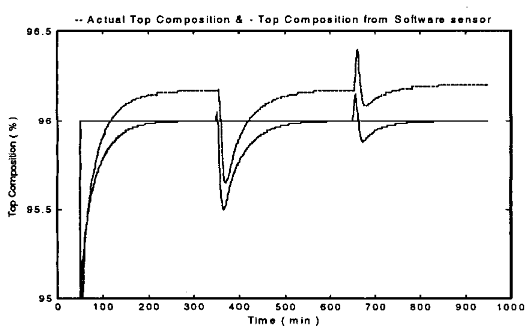


(a) without mean updating

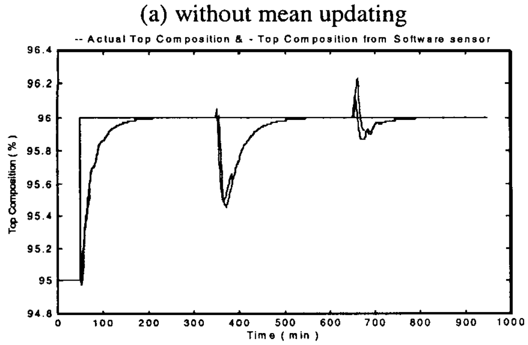


(b) with mean updating

Figure 8. Responses of bottom composition of the static PCR model based inferential feedback controller



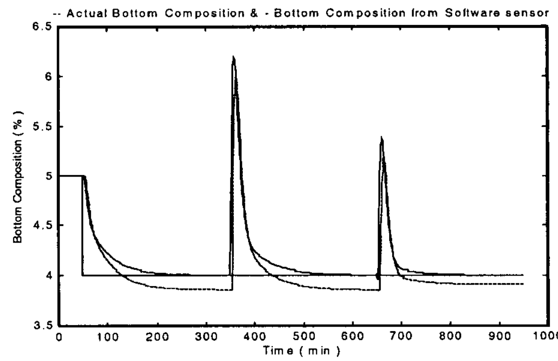
(a) without mean updating



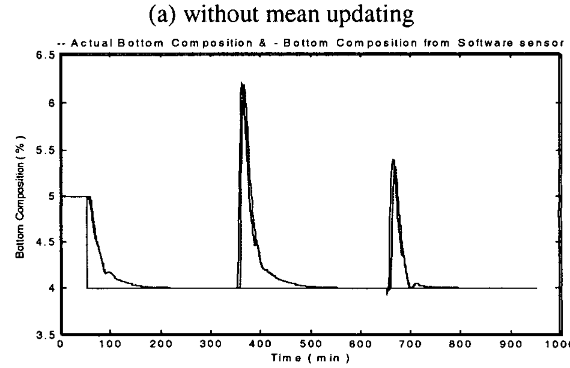
(b) with mean updating

Figure 9. Responses of top composition of the 2^{nd} order PCR model based inferential feedback controller

A problem in inferential control is that static control off-sets often exist due to static estimation errors. Zhang (2001) proposes using mean updating to eliminate static estimation and control off-sets. In this strategy, the process variable means are updated once a new steady state operating condition is detected. In such a way, the static estimation errors due to the operating condition drift can be eliminated. This strategy of mean updating is also used here. However, the studies of this paper show that the dynamic PCR inferential estimation models are more robust to process operating condition variations than the static PCR inferential estimation model.



(a) without mean updating



(b) with mean updating

Figure 10. Responses of bottom composition of the 2^{nd} order PCR model based inferential feedback controller

To investigate the performance of the inferential feedback control schemes under operating condition variations, the setpoints for the top and bottom product compositions were changed to 96% and 4% respectively, followed by feed rate and feed composition disturbances. Figures 7 and 8 shows, respectively, the top and bottom composition responses of the static PCR model based inferential feedback controller. Figures 9 and 10 shows, respectively, the top and bottom composition responses of the 2^{nd} order dynamic PCR model based inferential feedback controller. In these figures, the setpoints for the top and bottom compositions were changed to 96% and 4% respectively at the 51^{st} minutes and a 15%

increase in feed rate was introduced at the 351st minutes, followed by a 15% increase in feed composition at the 651st minutes. Through mean updating, steady state model estimation bias and the resulting control off-sets have been eliminated. However, it can be seen that the static PCR model has much larger estimation off-sets than the dynamic PCR model when the operating condition is changed. This demonstrates that the dynamic PCR model is more robust to process operating condition variations.

Table 4. SSE of different inferential control schemes

Control Schemes		Top Comp.	Bottom Comp.
static PCR model	without mean updating	322.4095	464.4818
	with mean updating	21.7258	137.7250
1st order dynamic PCR model	without mean updating	33.7257	107.5723
	with mean updating	23.3344	111.4505
2nd order dynamic PCR model	without mean updating	37.0658	97.9878
	with mean updating	22.9439	110.1967
3rd order dynamic PCR model	without mean updating	44.8958	97.1091
	with mean updating	22.6836	111.4769

Table 4 gives the SSE of different control schemes under the above setpoint changes and disturbances. It can be seen from Table 4 that the static PCR model based inferential feedback control scheme has much larger errors that the dynamic PCR model based inferential feedback control schemes. This indicates that the dynamic PCR models are more robust to operating condition variations than the static PCR model.

5. Conclusions

PCR static and dynamic models for distillation compositions are developed and used in inferential feedback control. It is shown that the PCR software sensor based composition control is superior to single tray temperature control and composition analyser based feedback control where substantial measurement delay exists. By using the PCR software sensors, substantial measurement delays can be eliminated and, hence, the close loop control performance is improved. By utilising multiple tray temperatures, enhanced correlation between tray temperatures and the top and bottom compositions can be achieved. Studies in this paper also show that the dynamic PCR models give more accurate estimations and are more robust to process operating condition variations than the static PCR model. Applications to a simulated methanol-water separation column demonstrate the effectiveness of the control strategy.

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