Simple Nonlinear Controller for High-Purity Distillation Columns

I-Lung Chien
Dept. of Chemical Engineering, Chang Gung College of Medicine and Technology, Kweishan, Taoyuan, Taiwan, R.O.C.
Yeong Tarng Tang and Tsun-Sheng Chang
Dept. of Chemical Engineering, Chung Yuan Christian University, Chung Li, Taoyuan, Taiwan, R.O.C.

As a distillation column is a very important unit operation in the chemical and petrochemical industry, many of the challenging problems associated with the design, operation, and control of distillation columns have been studied extensively. When the distillation columns are used for low-to-medium purity separation, the primary problem associated with the typical two-point product quality control is mainly due to the process interactions. Many acceptable techniques have been proposed for solving this and other related problems, some of which have attained a level of success in industrial applications.

With distillation columns used for high-purity separations, however, the situation is quite different. In addition to the usual process interaction problems, and possible operation constraints, these columns typically exhibit very strong asymmetric nonlinear behavior, and tend to be very ill-conditioned, too. Also, for most industrial columns, composition measurement are rarely available on-line; control is therefore often based on temperature measurements. The major issues involved in dual composition/temperature control of high-purity columns have been studied and reported in many applications. Some examples include: Fuentes and Luyben (1983); McDonald and McAvoy (1987); McDonald (1987); Georgiou et al. (1988); Skogestad and Morari (1988); Skogestad and Lundström (1990); Chang et al. (1992); Wang and Yu (1993); Sriniwas et al. (1995); Li and Lee (1996).

In Chien and Ogunnaike (1997), the possibility of using a linear model in a temperature-based control system is investigated for a high-purity column. While acceptable closed-loop performance can be obtained using a linear model in a model-predictive control (MPC) framework, the residual plant/model mismatch will still be significant enough that the resulting performance may, in fact, be no better than that obtainable from a well-tuned set of multiloop PID controllers. Thus, in our preceeding article (Chien, 1996) a simple form of an empirical nonlinear low-order dynamic model particularly suited for high-purity distillation columns is developed in order to reduce the plant/model mismatch. In this article, we then further utilize this nonlinear dynamic model into a nonlinear model predictive control framework. The resulting nonlinear controller, unlike most of the other nonlinear controllers in the literature, is very simple and can potentially be widely applicable in industrial environments.

Correspondence concerning this note should be addressed to I-L. Chien at the present address: Dept. of Chemical Engineering, National Taiwan University of Science and Technology, Taipei, Taiwan 106, R.O.C.

Column Process and the Empirical Nonlinear Model

The studies reported in this article were carried out using the distillation column model developed by Weischedel and McAvoy (1980). A simple empirical nonlinear model for temperature-based high-purity columns is developed with the following first-order differential equation vector form

$$\tau(Y)\frac{dY}{dt} = -Y + K(Y)U \tag{1}$$

where $Y = \text{col}[y_1, y_2]$ and $U = \text{col}[u_1, u_2]$ are the controlled variable and the manipulated variable vectors, respectively. $\tau(Y)$ is a diagonal process time constant matrix with the elements as nonlinear functions of the controlled variables. $K(Y)$ is a process gain full matrix with the elements also as nonlinear functions of the controlled variables.

The process gain and time constant variations are represented explicitly by the following empirical expressions suggested by the high-purity column process characteristics

$$k_{ij} = k_{ij}^0 + k_{ij}^1 \Delta y_i^{\text{top}} + k_{ij}^2 \Delta y_i^{\text{bot}} \tag{2}$$

$$\tau_{11} = \tau_{11}^0 + \tau_{11}^1 \Delta y_1^{\text{top}} \tag{3}$$

$$\tau_{22} = \tau_{22}^0 + \tau_{22}^1 \Delta y_2^{\text{bot}} \tag{4}$$

where the "driving force" terms (Δy_i^{top} and Δy_i^{bot}) show the relative difference in temperatures of measured tray temperatures to the two limiting high and low temperatures in the distillation column (T_{top} and T_{bot}) as defined in Chien (1996).

For more details of the process description and this nonlinear model form as well as some guidelines of how to obtain the model parameters, please refer to Chien (1996).

In this control study, we utilize $\pm 0.5\%$ and $\pm 2\%$ step response data from the column process while following the procedure outlined in Chien (1996) to obtain the model parameters associated with the process gain of this column as:

$$\begin{aligned} k_{11}^0 &= -29.11; & k_{11}^1 &= -31.07; & k_{11}^2 &= 67.71 \\ k_{12}^0 &= 30.40; & k_{12}^1 &= 33.03; & k_{12}^2 &= -67.61 \\ k_{21}^0 &= -36.54; & k_{21}^1 &= -80.67; & k_{21}^2 &= 73.43 \\ k_{22}^0 &= 40.44; & k_{22}^1 &= 85.11; & k_{22}^2 &= -73.55 \end{aligned}$$

and then using the eight dynamic curves from $\pm 0.5\%$ and $\pm 2\%$ step changes of u_1 and u_2 in respect to y_1 together with a nonlinear optimization routine (we used UMINF subroutine in IMSL library in this case) to obtain the model parameters associated with the process time constant of y_1 (τ_{11}^0 and τ_{11}^1). The objective function in the nonlinear optimization is defined to be

$$\min \sum_{n=1}^{8} \sum_{k=0}^{k} (y_{1,nk} - \hat{y}_{1,nk})^2$$

where n is the number of curves, k is the number of data points in a step-response curve, and $\hat{y}_1$ is the predicted value of y_1 from the nonlinear model.

The resulting model parameters associated with the process time constant of y_1 for this example are

$$\tau_{11}^0 = 89.90; \qquad \tau_{11}^1 = -87.36$$

Similar calculation for y_2 to get

$$\tau_{22}^0 = 146.52; \qquad \tau_{22}^1 = 101.38$$

The magnitudes of the open-loop step changes used in this article ($\pm 0.5\%$ and $\pm 2\%$) are smaller than the $\pm 1\%$ and $\pm 5\%$ used in Chien (1996). Smaller perturbations still can obtain a good enough model, and this is always a favorable alternative in any industrial applications.

Nonlinear Model Predictive Control Development

In what follows, the rigorous first principles model for the distillation column is used to represent the "plant." The objective is to evaluate the closed-loop behavior under model predictive control with the above simple empirical nonlinear model and to compare the result with conventional multiloop PID control. Only if the nonlinear controller produces enough benefit in comparing to the conventional approach, then we would consider implementing the control algorithm in industrial applications.

In all the closed-loop simulation follows, a one minute additional deadtime is assumed in the control loop to account for all the other time delays that are not considered in the rigorous column simulation (such as temperature sensor delay, control valve dynamics, and so on). In the multiloop PID implementation, tray No. 21 temperature is used to manipulate reflux flow rate, and tray No. 7 temperature is used to manipulated steam flow rate. In model predictive control scheme, instead, the multivariable controller will be implemented where both process outputs will be used to manipulate simultaneously the reflux and steam flow rates.

Control structure

The nonlinear model predictive controller (NMPC) used in this application is quite simple and easy to understand. The objective function of the NMPC is similar to Hernandez and Arkun (1993) in their polynomial ARX model NMPC implementation and subsequently applied to this column example in Sriniwas et al. (1995). The control action is calculated at each time step by minimizing the following objective function

$$\min_{\Delta U} \phi \sum_{i=1}^{P} E(k+i)^T \Gamma E(k+i) + \sum_{j=1}^{M} \Delta U(k+j-1)^T \Lambda \Delta U(k+j-1) \quad (5)$$

where

$$E(k+i) = Y^{sp}(k+i) - \hat{Y}(k+i) \qquad i = 1,2,\ldots,P \quad (6)$$

is the two-dimensional vector of deviation of the predicted process output $\hat{Y}$ from desired setpoint trajectory Y^{sp} over the "prediction horizon" P; ΔU is the change in the input over the "control horizon" M; Γ and Λ are the output and input weight matrices, respectively. The input $U(k+j)$ beyond the control horizon with $j \geq M$ is assumed to be equal to $U(k+M-1)$.

The predicted output $\hat{Y}$ is calculated in the following fashion

$$\hat{Y}(k+i) = \tilde{Y}(k+i) + D(k+i) \qquad i = 1,2,\ldots,P \quad (7)$$

where $\tilde{Y}(k+i)$ is the nonlinear model prediction of the controlled variable vector Y at time $k+i$. By using the nonlinear first-order model in Eq. 1 with an additional one minute deadtime for the reality purpose as mentioned earlier, this continuous time nonlinear model can be shown as

$$\tau(Y)\frac{d\tilde{Y}(t)}{dt} = -\tilde{Y}(t) + K(Y)U(t-1) \quad (8)$$

where $\tau(Y)$ and $K(Y)$ are both nonlinear functions of the measured controlled variable vector Y and will be updated at each time step. Each time the optimizer, Eq. 5, chooses the future manipulated variables, the future model prediction of the controlled variables over the prediction horizon will be integrated via Eq. 8.

$D(k+i)$ is added in Eq. 7 to account for any modeling mismatches and unmeasurable disturbances in the process. At time instant k with the actual measurement $Y(k)$ now available, the discrepancy in the model prediction, that is

$$D(k) = Y(k) - \tilde{Y}(k) \quad (9)$$

also becomes available. Since to minimize the objective function of Eq. 5, the vector of future values of $D(k+i)$ that are unknown at time instant k is needed; thus, they can only be estimated on the basis of currently available information and possibly the history of the past $D(k-i)$.

Disturbance estimation

In the traditional MPC implementation, this discrepancy $D(k)$ is assumed to be due to the effect of unmodeled disturbances yet unaccounted for by the model; it is further assumed that this is the best estimate of the future values of such disturbance effects. Thus, each element $D(k+i)$ is estimated as

$$D(k+i) = D(k) = Y(k) - \tilde{Y}(k); \qquad i = 1,2,\ldots,P \quad (10)$$

The strategy, although suitable for the process with a faster dynamic, will not perform well for processes with very long time constants (cf., Morari and Lee, 1991). It is now known that this problem can be dealt with effectively by appending the state estimation to the main MPC algorithm for more realistic prediction of the effect of unmodeled dynamics (cf., Ricker, 1990). The state estimation technique is quite complicated, especially to explain to plant personnel if a wider industrial application is sought. The algorithm is also quite computationally involved.

In this article, we use a much simpler strategy to estimate and update the unmodeled dynamics by utilizing the "most current two" discrepancy information as

$$D(k+i) = \alpha[D(k+i-1) - D(k+i-2)] + D(k+i-1); \qquad i = 1,2,\ldots,P \quad (11)$$

where α is an additional user-specified tuning parameter. This tuning parameter is normally between zero to one. When α is equal to zero, this strategy is reduced to the traditional approach of Eq. 10; with α equal to one, a "ramp" type unmodeled disturbance is assumed.

Closed-loop performance

Subroutine BCLSF in IMSL library is used to solve this optimization problem in Eqs. 5 to 11. The main tuning parameters in this nonlinear model predictive controller are P, M, Γ, Λ, and α. The choice of Γ other than the identity matrix is usually used to set the relative importance of one controlled variable vs. the other. In this study, the importance of tray No. 21 temperature is assumed to be the same as tray No. 7 temperature; thus, the Γ parameters is chosen to be a 2×2 identity matrix. The control horizon M is the number of future control actions that are calculated in the optimization step to reduce the predicted errors. In order to minimize the computational effort without sacrificing too much of the closed-loop performance, M is chosen to be one for simplicity purpose. The other three tuning parameters P, Λ, and α are tuned via numerous computer simulation to find the suitable tuning parameters.

In the following, several different setpoint and load responses of this nonlinear MPC (NMPC) with simple disturbance estimation strategy as Eq. 11 will be compared to conventional multiloop PID controllers as well as the traditional disturbance estimation scheme of NMPC with $\alpha = 0$. The tuning method used for the multiloop PID controllers is the one developed in Chien et al. (1996) where multiloop tuning based on an internal model control principle is used. For more detail of this multiloop PID tuning method, please refer to Chien et al. (1996). The resulting tuning parameters for this column system are: $K_{c_1} = -1.14$; $\tau_{i_1} = 9.1$ min; and $K_{c_2} = 1.23$, $\tau_{i_2} = 7.0$ min.

The setpoint and load responses tested in the simulations are:

Figure 1: $@t = 10$ min, y_1^{sp} from 0.0 to 0.05 and y_2^{sp} remains at 0.0.
Figure 2: $@t = 10$ min, y_2^{sp} from 0.0 to 0.05 and y_1^{sp} remains at 0.0.
Figure 3: $@t = 10$ min, y_2^{sp} from 0.0 to -0.05 and y_1^{sp} remains at 0.0.
Figure 4: $@t = 10$ min, feed composition from 0.5 to 0.4.

The tuning parameters used in both the nonlinear MPC controllers are: $P = 7$, $M = 1$; $\Gamma = I$, $\Lambda = 0.6I$ and traditional

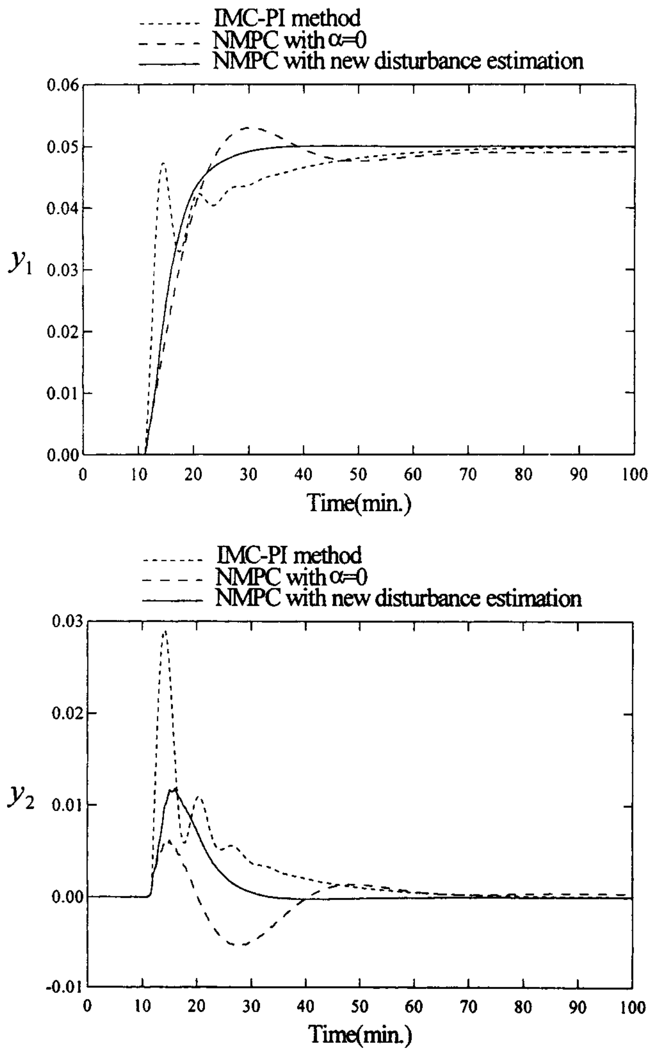

Figure 1. Comparison of controller performance y_1^{sp} from 0.0 to 0.05.

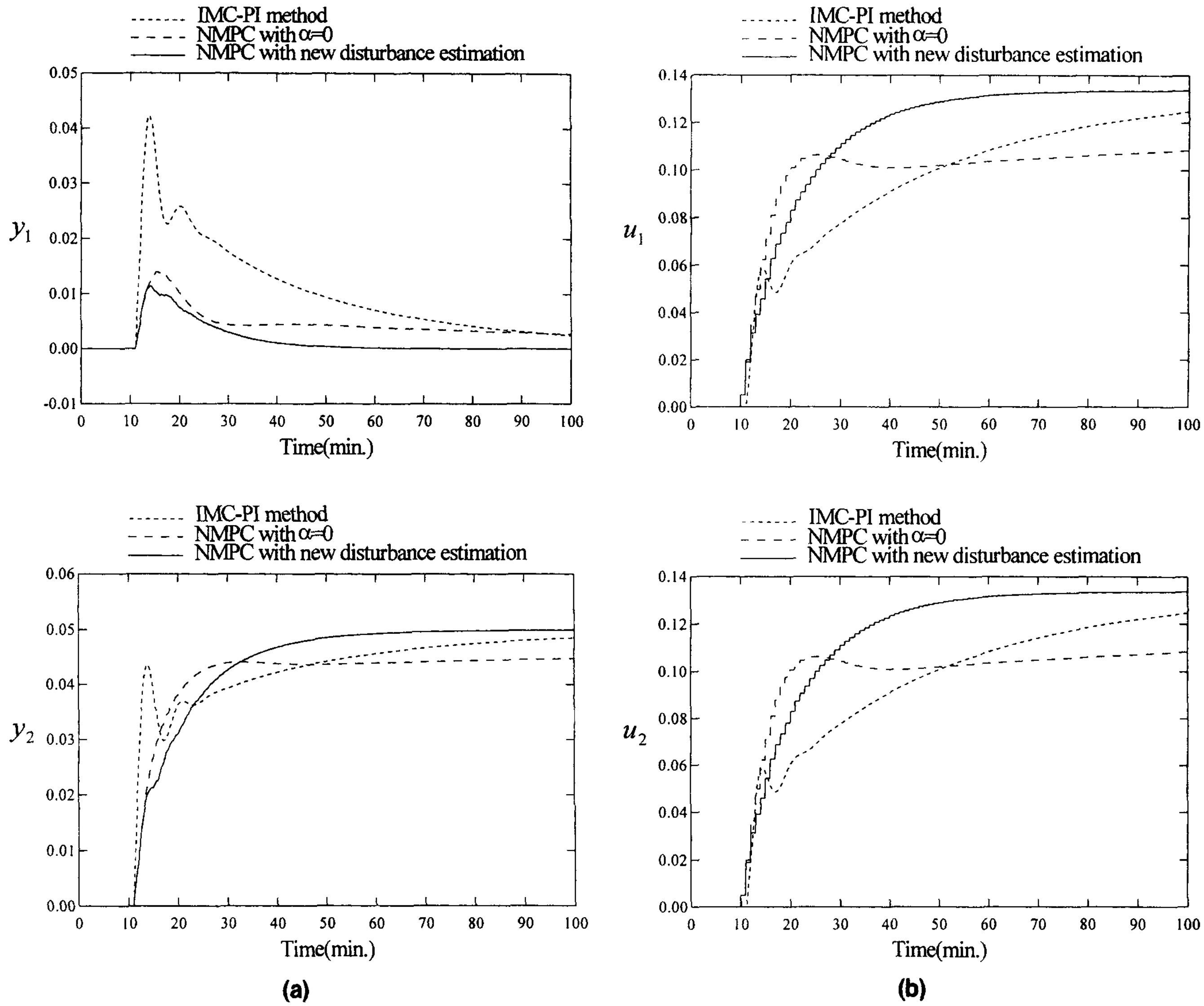

Figure 2. (a) Comparison of controller performance y_2^{sp} from 0.0 to 0.05; (b) manipulated variables of Figure 2a.

NMPC using $\alpha = 0.0$ and NMPC with new disturbance estimation using $\alpha = 0.99$.

Both setpoint and load responses are important because the setpoint of the controlled tray temperatures will adjust quite frequently to reflect the true top and bottom compositions once laboratory results become available. Figures 1 to 4 indicate that NMPC with $\alpha = 0.99$ provide much superior responses than the conventional multiloop PID controllers and NMPC with $\alpha = 0.0$. The interactions in the control system are handled well in this multivariable controller; this can be seen, for example, from the y_2 response in Figure 1. The nonlinearity of this system is also taken care of in the proposed NMPC controller; this can be seen from "similar" closed-loop responses of this NMPC for both $+0.05$ and -0.05 changes of, for example, y_2^{sp} in Figures 2a and 3a while the magnitude of the manipulated variables in Figures 2b and 3b are much different for the positive and negative setpoint changes.

Also noted in Figures 2a and 3a, the setpoint tracking ability of the NMPC with $\alpha = 0.0$ is extremely slow due to a very long open-loop time constant of this column system. On the other hand, the NMPC with a new disturbance estimation will give much faster servo responses due to better estimation of the modeling error. The ill-conditioning nature of the column can be seen from almost identical magnitudes of u_1 and u_2 in all of the setpoint changes (such as observed in Figures 2b and 3b). The load responses, which received the most criticism for conventional MPC performance especially for systems with very long time constants, are quite satisfactory. In all the closed-loop tests, the changes of the manipulated variables of the proposed nonlinear controller are very smooth which should be most desirable by the industrial users.

Another advantage of this NMPC strategy in comparison to other much more complicated nonlinear controllers is its simplicity in both the nonlinear model form and also the control implementation. The controller is much less computationally involved which is an important factor for any successful industrial implementations.

Due to page limitation, some of the manipulated variable changes as well as the results of other closed-loop runs such

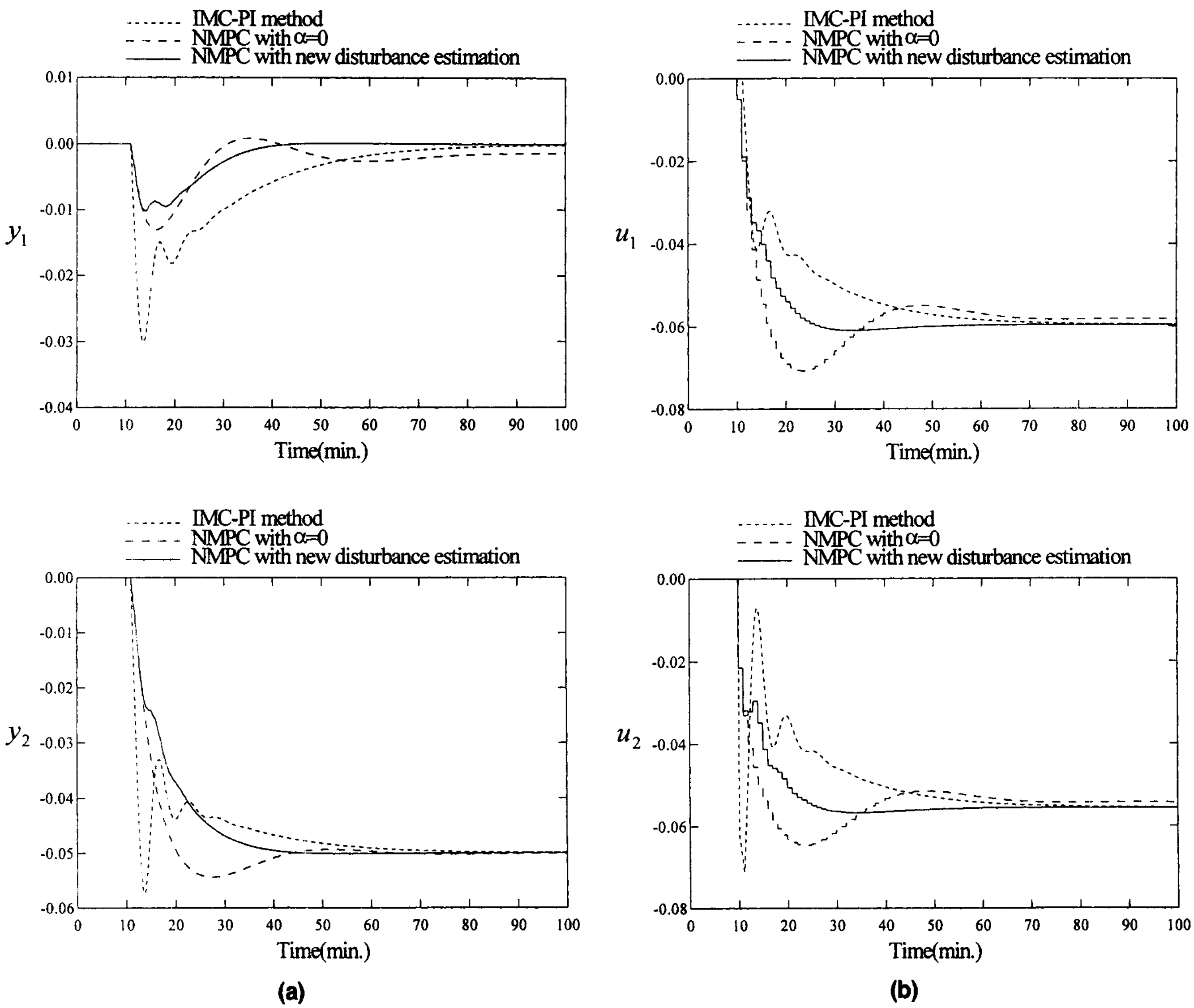

Figure 3. (a) Comparison of controller performance y_2^{sp} from 0.0 to −0.05; (b) manipulated variables of Figure 3a.

as negative setpoint change in y_1 and positive feed composition changes are not shown here. The closed-loop performances of the NMPC with new disturbance estimation in these runs are all much superior than the others.

Compare to published results

The closed-loop results of this nonlinear controller can also be directly compared to the results of a recently published article by Li and Lee (1996). In the article, they proposed a frequency-domain closed-loop identification method to obtain a reliable nonparametric frequency response model and applied their method to the same column studied in this article. In their closed-loop simulation runs, they used the dynamic matrix controllers (DMC) formulated as in Lee et al. (1994) with the impulse response coefficients obtained from their proposed identification method. They also show the closed-loop results of DMC using the theoretical model from rigorous column simulation, which normally is not available in industrial applications but can treat as best achievable closed-loop performance for the purpose of comparison. Their setpoint tracking results can be found in Figures 12, 13, 16, and 17 of their article. These figures can be directly compared to our Figures 1 and 2. From these figures, we can clearly see that our proposed controller gives better closed-loop performance. Notice also that in Li and Lee's closed-loop simulations, they did not include the one minute additional deadtime in the loop which is added in our simulation runs to reflect true column applications. This additional deadtime will make their closed-loop response slightly more inferior.

The above comparison is to the best possible linear model predictive control like the DMC used in Li and Lee (1996). We also compared the results of this simple nonlinear controller to the one by Sriniwas et al. (1995), which they utilized nonlinear ARX model to design a nonlinear controller. Their closed-loop setpoint tracking and disturbance rejection results can be seen in Figures 17, 18, 24 and 25 of their article. These results can be compared to Figures 2, 3, and 4 of our article. Again, our proposed controller gives better closed-loop responses. In Sriniwas et al. (1995), they need to utilize

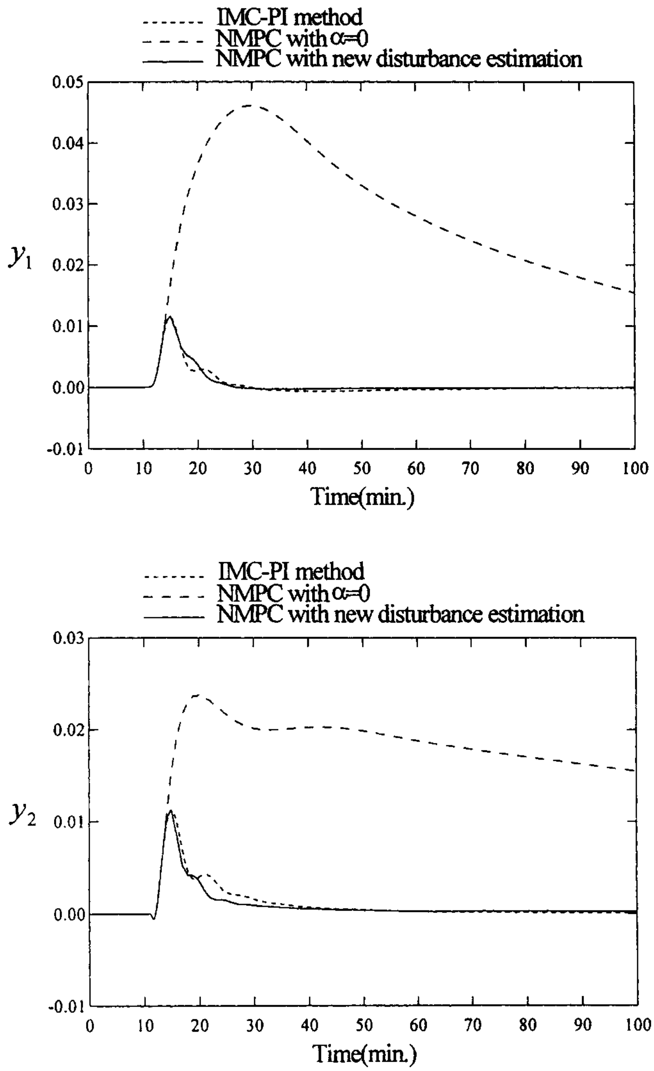

Figure 4. Comparison of controller performance (feed composition from 0.5 to 0.4).

state estimation as well as a model parameter updating scheme to give the closed loop as shown in their article; thus, the computational effort is much greater than our proposed controller. Also, again, that one minute additional deadtime is not included in their simulation runs; thus, their closed-loop responses will be worse if this deadtime is added.

Conclusion

A very simple nonlinear controller is proposed to control the product quality of high-purity distillation columns. The nonlinear model used in the controller is a very simple empirical low-order type which is capable of representing the nonlinearities inherent in these processes quite adequately. The controller is in the framework of model predictive control. A simple unmodeled disturbance estimation scheme is used to improve the load response significantly. This nonlinear model predictive control scheme is quite simple and easy to implement, which can potentially be attractive to industrial users. From various setpoint tracking and disturbance rejection tests of a rigorous distillation column, this controller shows excellent closed-loop performance.

Acknowledgments

This work is supported by the National Science Council of R.O.C. under grant NSC 85-2214-E-182-003. The rigorous distillation column model used in this study was provided by Prof. T. J. McAvoy at the University of Maryland.

Literature Cited

Chang, C. M., S. J. Wang, and S. W. Yu, "Improved DMC Design for Nonlinear Process Control," *AIChE J.*, **38**, 607 (1992).

Chien, I-L., "Simple Empirical Nonlinear Model for Temperature-Based High-Purity Distillation Columns," *AIChE J.*, **42**, 2692 (1996).

Chien, I-L., M. E. Kuo, and S. W. Yu, "A Simple TITO PI Tuning Method Suitable for Industrial Applications," *Symp. on Computer Process Control*, Taipei, Taiwan, p. 24 (Dec., 1996).

Chien, I-L., and B. A. Ogunnaike, "Modeling and Control of a Temperature-Based High-Purity Distillation Column," *Chem. Eng. Comm.*, **158**, 71 (1997).

Fuentes, C., and W. L. Luyben, "Control of High-Purity Distillation Columns," *Ind. Eng. Chem. Process Des. Dev.*, **22**, 361 (1983).

Georgiou, A., C. Georgakis, and W. L. Luyben, "Nonlinear Dynamic Matrix Control of High-Purity Distillation Columns," *AIChE J.*, **34**, 1287 (1988).

Hernandez, E., and Y. Arkun, "Control of Nonlinear Systems Using Polynomial ARMA Models," *AIChE J.*, **39**, 446 (1993).

Lee, J. H., M. Morari, and C. E. Garcia, "State-Space Interpretation of Model Predictive Control," *Automatica*, **30**, 707 (1994).

Li, W., and J. H. Lee, "Frequency-Domain Closed-Loop Identification of Multivariable Systems for Feedback Control," *AIChE J.*, **42**, 2813 (1996).

Luyben, W. L., "Sensitivity of Distillation Relative Gain Arrays to Steady-State Gains," *Ind. Eng. Chem. Res.*, **26**, 2076 (1987).

McDonald, K. A., "Performance Comparison of Methods for On-Line Updating of Process Models for High-Purity Distillation Control," AIChE Meeting, Houston (April, 1987).

McDonald, K. A., and T. J. McAvoy, "Application of Dynamic Matrix Control to Moderate and High-Purity Distillation Towers," *Ind. Eng. Chem. Res.*, **26**, 1011 (1987).

Morari, M., and J. H. Lee, "Model Predictive Control: the Good, the Bad, and the Ugly," CPC IV, South Padre Island (Feb., 1991).

Ricker, N. L., "Model Predictive Control with State Estimation," *Ind. Eng. Chem. Res.*, **29**, 374 (1990).

Skogestad, S., and P. Lundstrom, "Mu-Optimal LV-Control of Distillation Columns," *Computers Chem. Eng.*, **14**, 401 (1990).

Skogestad, S., and M. Morari, "LV-Control of a High-Purity Distillation Column," *Chem. Eng. Science*, **43**, 33 (1988).

Sriniwas, G. R., Y. Arkun, I-L. Chien, and B. A. Ogunnaike, "Nonlinear Identification and Control of a High-Purity Distillation Column: A Case Study," *J. Process Cont.*, **5**, 149 (1995).

Wang, S. J., and S. W. Yu, "Robust Feedback Design for Nonlinear High-Purity Distillation Column Control," *Comput. Chem. Eng.*, **17**, 897 (1993).

Weischedel, K., and T. J. McAvoy, "Feasibility of Decoupling in Conventionally Controlled Distillation Columns," *Ind. Eng. Chem. Fund.*, **19**, 379 (1980).

Manuscript received Nov. 18, 1996, and revision received May 15, 1997.