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Polymer Property Control in a Continuous Styrene Polymerization Reactor Using Model-on-Demand Predictive Controller

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Abstract–The model-on-demand (MoD) framework was extended to the model predictive control (MPC) to design a multiple variable model-on-demand predictive controller (MoD-PC). This control algorithm was applied to the property control of polymer product in a continuous styrene polymerization reactor. For this purpose, a local auto-regressive exogenous input (ARX) model was constructed with a small portion of data located in the region of interest at every sample time. With this model an output prediction equation was formulated to calculate the optimal control input sequence. Jacket inlet temperature and conversion were chosen as the elements of regressor state vector in data searching step. Simulation studies were conducted by applying the MoD-PC to MIMO control problems associated with the continuous styrene polymerization reactor. The control performance of the MoD-PC was then compared with that of a nonlinear MPC based on the polynomial auto-regressive moving average (ARMA) model for disturbance rejection as well as for setpoint-tracking. As a result, the MoD-PC was found to be an effective strategy for the production of polymers with desired properties.

Key words: Model-on-Demand (MoD), Predictive Control, Polymer Property Control, Styrene Polymerization, Continuous Reactor

INTRODUCTION

One of the important goals of polymerization reactor operation is the production of a polymer having desired properties for a specific application. For this reason, the property control of polymer product in polymerization reactors has been the subject of a large number of research works [Schork et al., 1993; Embirucu et al., 1996]. However, it still remains as a difficult task because of the complex reaction mechanism, the dramatic increase in the viscosity of reaction mixture and the highly nonlinear nature of polymerization processes.

In most of the previous works, the use of model-based control has been proven more effective than other control strategies. Perhaps the most important factor to be considered in model-based control is the acquisition of an accurate model, which should not only be able to capture the system dynamics but also be easily incorporated in the controller design and realization. The first-principles model of a polymerization reactor contains a large number of kinetic parameters, which are neither readily found from the literature nor easily determined by experiments. Therefore, various types of empirical models are suggested for the identification of polymerization reactors and used in the design of model-based control as an alternative to the first-principles model.

Since linear models fail to predict the nonlinear behavior of a polymerization reactor, it is recommended to use nonlinear models in the control of polymer properties. Indeed, a good number of studies on nonlinear control have been carried out in this regard. Fruzzetti et al. [1995] employed the Hammerstein model in their NLMPC scheme, while Maner and Doyle III [1997] used the autoregressive plus Volterra model to identify a continuous methyl methacrylate (MMA) polymerization reactor and implemented the model in the NLMPC. Cho et al. [1999] applied the Takagi-Sugeno type fuzzy model based model predictive control scheme to the control of the nonlinear pH neutralization process. Hernandez and Arkun [1993] considered a single-input and single-output (SISO) polynomial ARMA model to identify a continuous stirred tank reactor (CSTR), in which a first-order exothermic reaction occurred, and proposed a nonlinear MPC scheme based on the identified polynomial ARMA model. Na and Rhee [2000, 2002] designed a nonlinear MPC based on the identified polynomial ARMA model by using the successive linearization method for the control of conversion and weight-average molecular weight in a continuous styrene polymerization reactor. These authors [2002] also implemented experimentally their MPC algorithm to a continuous styrene polymerization reactor. Nonlinear models, however, present some difficulties in the identification and optimization for the controller. The optimization problem requires sophisticated, time-consuming methods and is numerically very difficult [Henson, 1998].

The concept of model-on-demand (MoD) is a novel paradigm first proposed by Cybenko [1996] in the name of the 'just-in-time model'. Afterward, it was further developed and modified by Stenman [1999a, b] and Braun et al. [1999, 2000]. However, all of the applications have been restricted to SISO systems. The basic concept of MoD is to identify a local model with the data that belong to a small neighborhood around the current operating point rather than to estimate a complex global model covering the entire input-output domain. This algorithm provides a good fit by using a signif-

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‡This paper is dedicated to Dr. Youn Yong Lee on the occasion of his retirement from the Korea Institute of Science and Technology.

icantly simpler model than that for the global approximation. Hence, it provides the potential for the control performance rivaling those of global methods with less complex *a priori* knowledge, more reliable numerical computation and increasing flexibility.

In this study we introduce a local autoregressive exogenous input (ARX) model for the identification of a continuous styrene polymerization reactor. Then a model-on-demand predictive controller (MoD-PC) based on the identified ARX model is designed and applied to the property control of polymer product in the above-mentioned reactor.

MODEL-ON-DEMAND PREDICTIVE CONTROLLER (MoD-PC)

Model-on-demand is a data mining technology, taking advantage of increasing ability of computers to collect and manipulate large data sets. The basic principles behind the MoD philosophy are as follows: From the database of all the observation of lagged states, the relevant data are retrieved and they are applied to a suitable modeling operation whenever a model equation is needed. Details about the MoD can be found in Stenman [1999a].

The objective of data searching is to define the relevant data that are used for model parameter estimation. Among the state variables that have been stored in the database, we must constitute the regressor space by choosing the major variables that can describe the dynamics of the system. We then examine the regressor space and see if the states fall within the domain of a pre-specified distance from the current operating points. If so, the states within the domain are sorted. The state variables that correspond to the selected regressor states are also retrieved from the database. Various methods have been suggested for the definition of the distance function on which the shape and orientation of the neighborhood depend. In practice, the weighted Euclidian norm is most commonly chosen.

The local approaches that have been studied for a long time can also be utilized in the MoD framework easily. The main difference of the MoD framework as compared to the traditional statistical settings is that it considers the local data belonging to the neighborhood of the current state instead of the entire data. One of the practical uses of MoD technique is to incorporate it with the model-based control theory. Indeed, the MoD can be combined with the MPC formulation by obtaining a local model via the application of the MoD method at every sample time and minimizing the objective function constructed on the basis of the local model. If the local model is linear, the design of MoD-PC corresponds to that of the conventional linear MPC between two sample times.

CONTINUOUS STYRENE POLYMERIZATION REACTOR

The MoD-PC algorithm will be implemented for the property control of polymer product in a CSTR in which styrene polymerization occurs by the free radical mechanism. In the simulation study, the first-principles model developed for the jacketed CSTR is assumed to be the plant. The model equations are given in Na and Rhee [2000, 2002]. They consist of 11 equations describing the energy balances and the mass balances for the monomer, initiator, solvent, and the first three moments of both living and dead polymer concentrations and the equation for the total volume. The physical properties and the kinetic parameters are also taken from the same references. To take into account the gel effect, we use the empirical correlation suggested by Hamer et al. [1981]. The reference conditions for the simulation study are listed in Table 1.

Table 1. Reference conditions for the simulation study

Initial charge	Monomer (Styrene)	400 mL
	Solvent (Toulene)	400 mL
	Initiator (AIBN)	8 g
Feed concentration	Monomer	4.34 mol/L
	Solvent	4.70 mol/L
	Initiator	0.06 mol/L
Operating conditions	Reactor temperature	55-85 °C
	Feed flow rate	1-30 mL/min
Reactor dimension & conditions	Jacket volume (V_j)	0.8 L
	Feed temperature (T_f)	20 °C
	Ambient temperature (T_a)	20 °C
	Initiator efficiency (f_i)	0.5
	Heat of reaction for thermal conductance	74,500 cal/mol
	Heating or cooling water flow rate (q_c)	2.5 L/min

For property control, the jacket inlet temperature T_{jin} and the feed flow rate q_f are taken as the manipulated variables, while the conversion X and the weight-average molecular weight Mw are chosen as the controlled variables.

In order to reduce the differences among the orders of magnitude, the inputs and outputs are normalized between 0 and 1 as follows:

$$u_1=\frac{T_{jin}-T_{jin\,min}}{T_{jin\,max}-T_{jin\,min}} \qquad u_2=\frac{q_f-q_{f\,min}}{q_{f\,max}-q_{f\,min}}$$

$$y_1=X \qquad y_2=\frac{M_w-M_{w\,min}}{M_{w\,max}-M_{w\,min}} \tag{1}$$

The maximum and minimum values for individual variables are summarized in Table 2. The upper and lower bounds on the jacket inlet temperature are imposed as constraints, considering the heat transfer limitations and the safety. Similarly, the upper and lower bounds in the feed flow rate are defined as constraints to avoid the

Table 2. Scaling factors and constraints for input and output variables

Weight-average molecular weight (M_w, y_2)	$M_{w\,min}$	10000
	$M_{w\,max}$	40000
Jacket inlet temperature (T_{jin}, u_1)	$T_{jin\,min}$	55 °C
	$T_{jin\,max}$	85 °C
Feed flow rate (q_f, u_2)	$q_{f\,min}$	1 mL/min
	$q_{f\,max}$	30 mL/min
Input rate constraint of jacket inlet temperature (ΔT_{jin}, Δu_1)		−2~2 °C
Input rate constraint of feed flow rate (Δq_f, Δu_2)		−1~1 mL/min

negative flow rate and to set the maximum flow rate that can be handled by the pump.

DESIGN OF MoD-PC

In this study, we designed an MoD-PC and compared the performance of MoD-PC with those of an LMPC and an NLMPC designed on the basis of the polynomial ARMA model [Na and Rhee, 2000, 2002]. Before explaining how to design the MoD-PC, it seems helpful to review the design procedure of the NLMPC.

A multivariable polynomial ARMA model has the following structure

$$\begin{aligned} y_i(k) = y_{i0} &+ \sum_{l=1}^{q_y}\sum_{j=1}^{n_y} \theta_{l,j}^{1,i} y_l(k-j) + \sum_{l=1}^{q_u}\sum_{j=1}^{n_u} \theta_{l,j}^{2,i} u_l(k-j) \\ &+ \sum_{l=1}^{q_y}\sum_{j=1}^{n_y}\sum_{m=1}^{q_y}\sum_{n=1}^{j} \theta_{l,j,m,n}^{3,i} y_l(k-j) y_m(k-n) \\ &+ \sum_{l=1}^{q_u}\sum_{j=1}^{n_u}\sum_{m=l}^{q_u}\sum_{n=1}^{j} \theta_{l,j,m,n}^{4,i} u_l(k-j) u_m(k-n) \\ &+ \sum_{l=1}^{q_y}\sum_{j=1}^{n_y}\sum_{m=1}^{q_u}\sum_{n=1}^{n_u} \theta_{l,j,m,n}^{5,i} y_l(k-j) u_m(k-n) + \cdots \end{aligned} \tag{2}$$

where q_y and q_u denote the number of outputs and inputs, respectively, while n_y and n_u indicate the number of lags on the outputs and inputs, respectively. The order of nonlinearities was determined to be of second-order while both n_y and n_u were specified as 3. Although the model parameters were easily obtained by using the linear least-square error method, model structuring was required before this procedure. Since the number of possible regressors in the model equation is much larger than those in other models, only the significant regressors were selected among all the possible ones by using the stepwise model building algorithm. In fact, this is unnecessary in the linear model identification. Then the state-space realization method was employed to facilitate the construction of the nonlinear controller.

If the ARMA model is directly used in the MPC design, the objective function becomes a higher order function of input variables because of the nonlinearities of the polynomial ARMA model structure. Accordingly, it requires a large time in optimal input. Na and Rhee [2002] employed the EKF-based NLMPC scheme to make the optimization problem be solved by quadratic programming. Hence, the output prediction equation for *p*-sampling intervals into the future was constructed by performing forward iteration and successive linearization of the state equation.

In the MoD-PC, instead of identifying a global nonlinear model with a great deal of effort and linearizing it with respect to the regressor states at every sample time, we identify a local linear model with the data near the current state at every sample time. In other words, we describe the system with a local linear ARX model instead of the second order nonlinear polynomial ARMA model. Here, the number of lags on the outputs and inputs is adopted as three for both models.

1. Construction of the Regressor Space and the Data Space

Among the input and output pairs, the structural elements of regressor state vector $\varphi(k)$ are selected with the normalized input-output pairs; *i.e.*, three step lagged T_{jin} and X. From the physical perspective those states are the most reflective of the system dynamics, and the three step lagged T_{jin} and X are used for the reflection of the past trajectory of the dynamics. The weighted Euclidean norm is used as the distance function to select the relevant data from the regressor space; *i.e.*, $d(\varphi(k), \varphi(\cdot)) = \sqrt{[\varphi(k)-\varphi(\cdot)]\mathbf{M}[\varphi(k)-\varphi(\cdot)]^T}$. The weighting matrix **M** is assumed to be diagonal for convenience. The values of the matrix are determined by the trial and error method by the criterion that larger values are assigned to the recent elements of the regressor state vector and similar values are assigned to the recent elements for T_{jin} and X to give a similar effect on the distance function. As for the tuning of b, it is worth noting that there exists a trade-off between bias and variance. Several classical methods such as the False Nearest Neighborhood (FNN) method, cross-validation and Akaike Information Criteria (AIC) are used in the determination of the distance criterion b and the value may be a function of time. However, the value of b was kept constant and chosen by the trial and error method in our work. In the data retrieval step, the data within the distance criterion b from the current state in the regressor space are selected.

$$\begin{aligned} &\varphi(k)=[y_1(k)\ y_1(k-1)\ y_1(k-2)\ u_1(k-1)\ u_1(k-2)\ u_1(k-3)] \\ &\mathbf{M}=\mathrm{diag}(2,\ 1.5,\ 1,\ 2.5,\ 1.9,\ 1.5) \\ &b=0.6\ (\text{case 1}),\ 0.4\ (\text{case 2}),\ 0.3\ (\text{case 3}) \end{aligned} \tag{3}$$

For the design of MoD-PC, the database which is composed of the regressor states and the input-output data is generated by imposing the pseudo random 8-level input signals to the first-principles model and saving the responses for a period of 2000 minutes. In this case, the sample time is 2 min and the switching probability P_s, which represents the probability of input change at the end of any sampling interval, is set equal to 0.05. Since the performance of MoD-PC is largely dependent on the quality and the number of data, it is important to make the data contain much information about the reactor dynamics. It is desired to use more frequently changed input signals with many levels and to save the responses during a prolonged time for a sufficient supply of data. Fig. 1 shows the generated initial data.

2. Model Structure and Controller Design

In this study, we shall consider the ARX model [Ljung, 1999; Yoo et al., 2002] of 3rd order for both inputs and outputs. Since the system has 2-inputs and 2-outputs, the model equation can be expressed as

$$\begin{aligned} &\mathbf{y}(k)=[y_1(k)\ y_2(k)]^T \quad \mathbf{u}(k)=[u_1(k)\ u_2(k)]^T \\ &\mathbf{y}(k)=\mathbf{A}(k)\mathbf{y}(k-1)+\mathbf{B}(k)\mathbf{y}(k-2)+\mathbf{C}(k)\mathbf{y}(k-3) \\ &\qquad +\mathbf{D}(k)\mathbf{u}(k-1)+\mathbf{E}(k)\mathbf{u}(k-2)+\mathbf{F}(k)\mathbf{u}(k-3) \end{aligned} \tag{4}$$

The elements of 2×2 matrices, **A**(k), **B**(k), **C**(k), **D**(k), **E**(k) and **F**(k), are determined by using the least square error method. For the sake of simplicity in calculation, $y_1(k)$ and $y_2(k)$ are assumed to be decoupled in the model equation since they are not strongly correlated, and hence **A**(k), **B**(k), and **C**(k) are used in diagonal form. The model parameters are obtained all at once by using the pseudo inverse that makes the parameter estimation procedure straightforward.

For an effective design of the model predictive controller, the model equation is reconstructed to the state-space model. This is necessary because the MIMO structure of the ARX model contains quite a large number of terms in the prediction. Thus we have

$$\mathbf{x}_{k+1}=\mathbf{A}_k\mathbf{x}_k+\mathbf{B}_k\mathbf{u}_k,\ \mathbf{y}(k)=\mathbf{C}_k\mathbf{x}_k$$

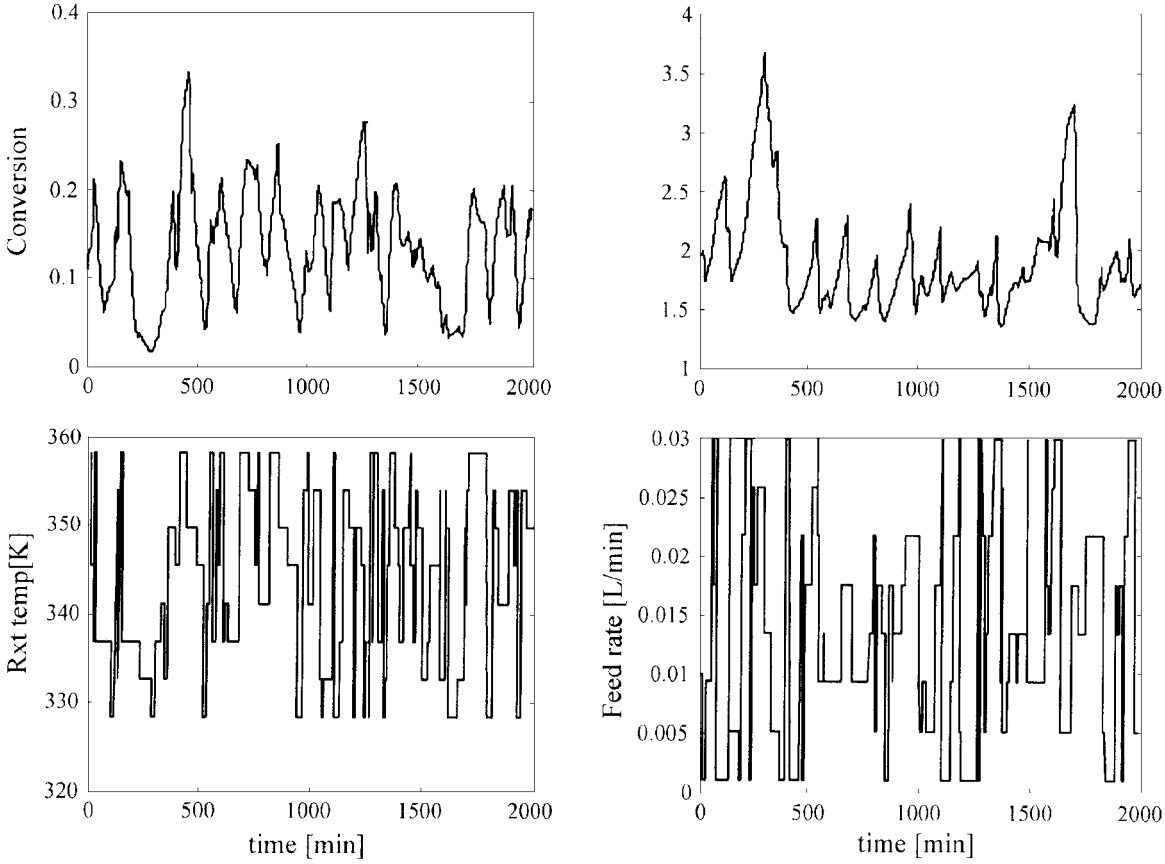

Fig. 1. Generated input/output data for the identification.

$$\mathbf{x}_k=[\mathbf{y}(k)^T\,\mathbf{y}(k-1)^T\,\mathbf{y}(k-2)^T]^T,\ \mathbf{u}_k=[\mathbf{u}(k)^T\,\mathbf{u}(k-1)^T\,\mathbf{u}(k-2)^T]^T$$

$$\mathbf{A}_k=\begin{bmatrix}\mathbf{A}(k) & \mathbf{B}(k) & \mathbf{C}(k)\\ I & 0 & 0\\ 0 & I & 0\end{bmatrix},\ \mathbf{B}_k=\begin{bmatrix}\mathbf{D}(k) & \mathbf{E}(k) & \mathbf{F}(k)\\ 0 & 0 & 0\\ 0 & 0 & 0\end{bmatrix},\ \mathbf{C}_k=\begin{bmatrix}I & 0 & 0\end{bmatrix} \tag{5}$$

With this state-space model one can derive the *p*-step prediction equation as follows:

$$Y_{k+1|k}=\begin{bmatrix}\hat{\mathbf{y}}(k+1/k)\\ \hat{\mathbf{y}}(k+2/k)\\ \vdots\\ \hat{\mathbf{y}}(k+p/k)\end{bmatrix}=\begin{bmatrix}\mathbf{C}_k\mathbf{A}_k\\ \mathbf{C}_k\mathbf{A}_k^2\\ \vdots\\ \mathbf{C}_k\mathbf{A}_k^p\end{bmatrix}\mathbf{x}_k+\begin{bmatrix}\mathbf{C}_k\mathbf{B}_k\\ \mathbf{C}_k\mathbf{A}_k\mathbf{B}_k+\mathbf{C}_k\mathbf{B}_k\\ \vdots\\ \sum_{i=0}^{p-1}\mathbf{C}_k\mathbf{A}_k^i\mathbf{B}_k\end{bmatrix}\mathbf{u}_k$$

$$+\begin{bmatrix}\mathbf{C}_k\mathbf{B}_k & 0 & \cdots & 0 & 0\\ \mathbf{C}_k\mathbf{A}_k\mathbf{B}_k+\mathbf{C}_k\mathbf{B}_k & \mathbf{C}_k\mathbf{B}_k & \cdots & 0 & 0\\ \vdots & \vdots & O & \vdots & \vdots\\ \sum_{i=0}^{p-1}\mathbf{C}_k\mathbf{A}_k^i\mathbf{B}_k & \sum_{i=0}^{p-2}\mathbf{C}_k\mathbf{A}_k^i\mathbf{B}_k & \cdots & \sum_{i=0}^{p-m}\mathbf{C}_k\mathbf{A}_k^i\mathbf{B}_k & \sum_{i=0}^{p-m-1}\mathbf{C}_k\mathbf{A}_k^i\mathbf{B}_k\end{bmatrix}\cdot\Delta\mathbf{U}_k$$

$$=\tilde{Y}_k+S_k\Delta\mathbf{U}_k \tag{6}$$

where $\Delta\mathbf{U}_k=[\Delta\mathbf{u}(k)^T,\ \ldots,\ \Delta\mathbf{u}(k+m-1)^T]^T$ denotes the rate of input changes within the control horizon m.

We shall consider the following objective function and input-output constraints:

$$\min_{\Delta U_k}\{\|\Lambda_y[Y_{k+1|k}-R_{k+1|k}]\|_2^2+\|\Lambda_{\Delta u}\Delta\mathbf{U}_k\|_2^2\} \tag{7}$$

subject to $\mathbf{u}(k+l)_{min}\le\mathbf{u}(k+l)\le\mathbf{u}(k+l)_{max},\ 0\le l\le m-1$

$-\Delta\mathbf{u}(k+l)_{max}\le\Delta\mathbf{u}(k+l)\le\Delta\mathbf{u}(k+l)_{max},\ 0\le l\le m-1$

$\mathbf{y}(k+l)_{min}\le\hat{\mathbf{y}}(k+l/k)\le\mathbf{y}(k+l)_{max},\ 1\le l\le p$

in which $R_{k+1|k}$ denotes the future reference vector, and Λ_y and $\Lambda_{\Delta u}$ represent the weighting matrices for the output and the input, respectively. As usual, p and m denote the prediction horizon and the control horizon, respectively. The computed input moves are implemented in the receding horizon fashion, and the optimization procedure is repeated at the next sampling interval.

APPLICATION TO POLYMER PROPERTY CONTROL IN A CONTINUOUS STYRENE POLYMERIZATION REACTOR

Simulations are conducted for disturbance rejection as well as for setpoint-tracking in a continuous styrene polymerization reac-

Table 3. Numerical values for the controller parameters

		p	m	Λ_u	Λ_y
NLMPC	Case1	20	3	diag(5, 5)	diag(20, 10)
	Case2	20	3	diag(20, 5)	diag(20, 15)
	Case3	20	8	diag(10, 10)	diag(30, 30)
MoD-PC	Case1	20	5	diag(5, 5)	diag(20, 30)
	Case2	20	3	diag(5, 5)	diag(30, 30)
	Case3	10	3	diag(5, 5)	diag(30, 20)

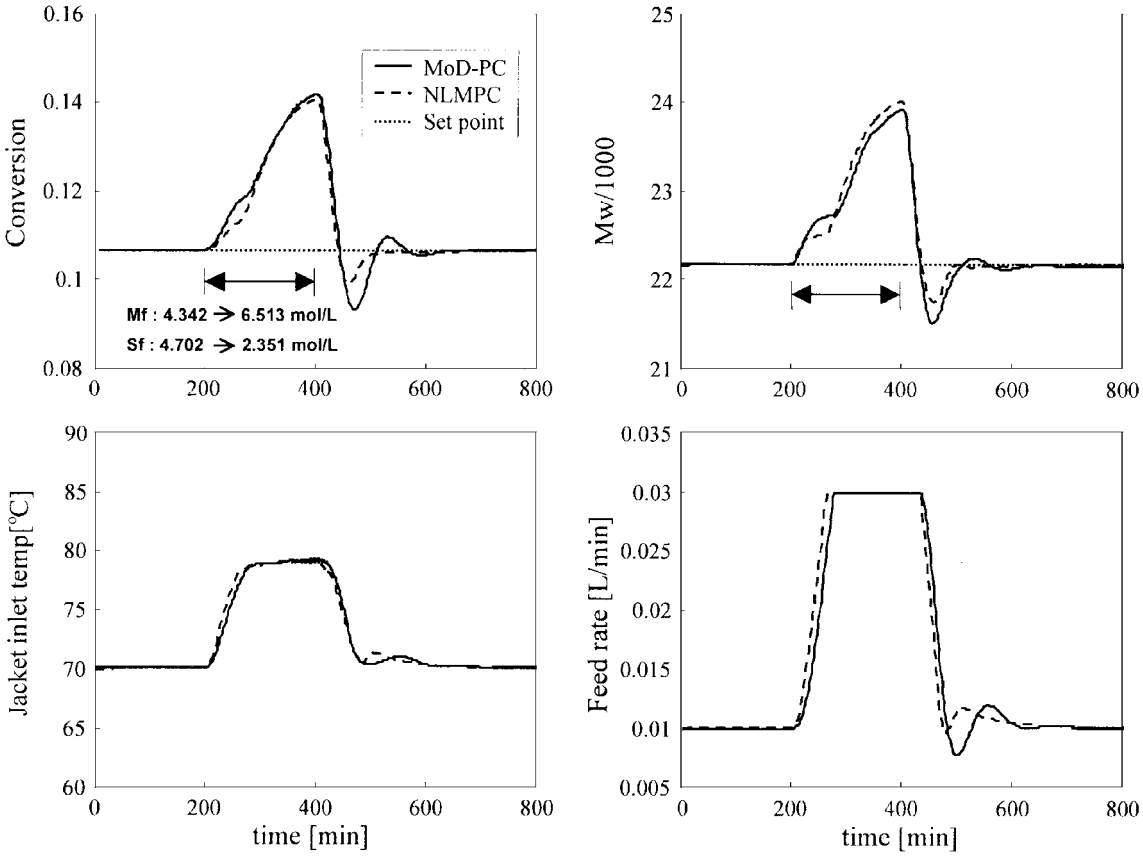

Fig. 2. Regulatory performances of the MoD-PC and the NLMPC (Case 1).

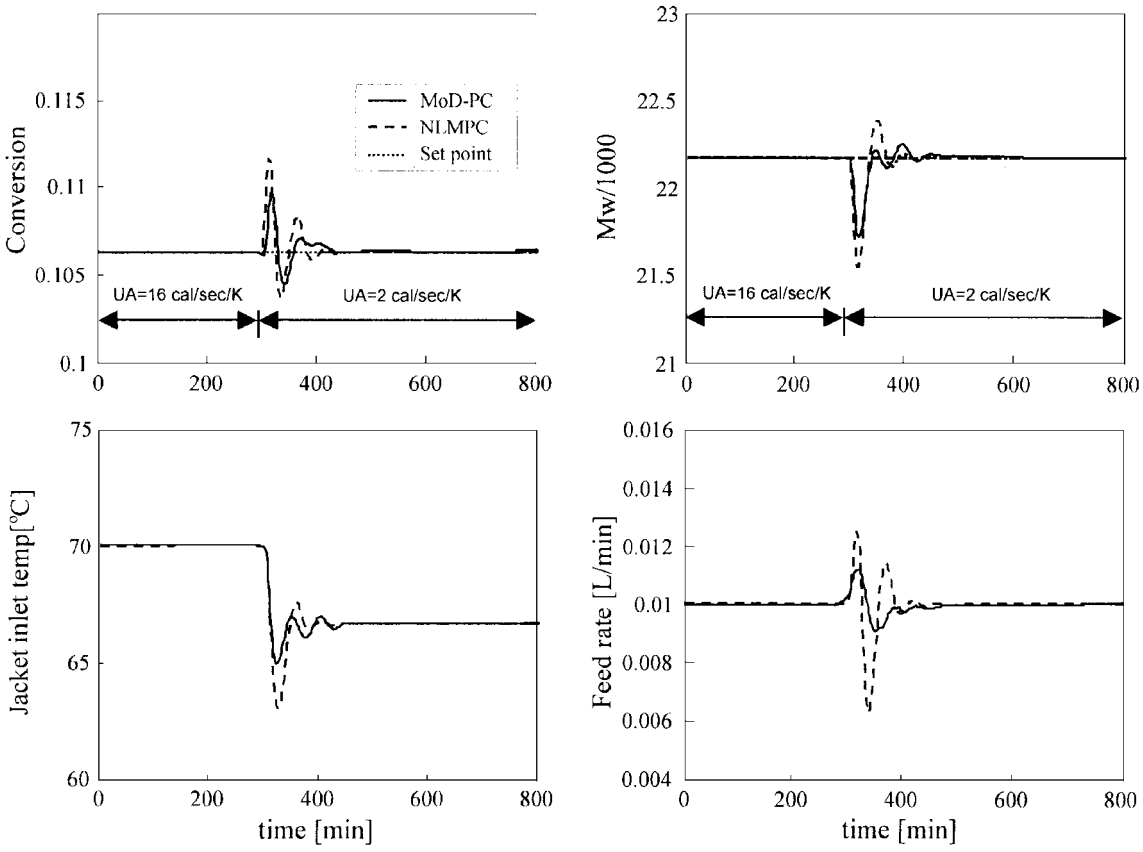

Fig. 3. Regulatory performances of the MoD-PC and the NLMPC (Case 2).

tor. The control performance of the proposed MoD-PC is compared to that of a nonlinear MPC, which is designed on the basis of the polynomial ARMA model. The sample time is 2 min, and the prediction and control horizons are given in Table 3. The weighting matrices used in the MoD-PC and the nonlinear MPC are determined by trial-and-error and listed in Table 3 for each of the cases investigated. The tuning of the design variables depends on both the type of the controller applied to the system and the condition under which a simulation is conducted. The design variables are retuned and therefore different optimal values are selected for each case study and for each controller.

1. Disturbance Rejection Problem

The ability of disturbance rejection is corroborated by analyzing two extreme cases: one with a fluctuation of the feed concentrations (Case 1) and the other with a sudden change in the thermal conductance UA (Case 2).

In Case 1, it is assumed that the monomer feed concentration is increased from 4.342 to 6.513 mol/L between 200 and 400 min, while the solvent feed concentration is decreased from 4.702 to 2.351 mol/L during the same period. Fig. 2 presents the regulatory performances of the MoD-PC and the nonlinear MPC. Since the monomer concentration is increased, both the conversion and the weight average molecular weight are increased from their steady values. During the presence of disturbance, the MoD-PC eliminates the effect of disturbance as satisfactorily as the nonlinear MPC does. After the feed concentrations recover their steady values, the MoD-PC shows a somewhat oscillatory behavior and registers a larger overshoot. All in all, however, the performance of the MoD-PC is quite comparable to that of the nonlinear MPC.

For the Case 2, let us consider that the thermal conductance UA is decreased from 16 to 2 cal/sec K because of the fouling after 300 min of reaction time. As shown in Fig. 3, the decrease in the rate of heat transfer gives rise to an increase in the conversion and a decrease in the molecular weight from their respective steady values. In order to reject the effect of the disturbance, the MoD-PC decreases the jacket inlet temperature and raises the feed flow rate simultaneously. As a result, the controller drives the controlled outputs to their respective setpoints despite the presence of a severe disturbance. It is worth noting that the decrease in the thermal conductance has been ultimately compensated by a decrease in the jacket inlet temperature without a significant change in the feed rate.

For comparison, the simulation result obtained with the nonlinear MPC is also presented in Fig. 3. The nonlinear MPC results in a large overshoot. However, it drives the controlled outputs to their setpoints more quickly due to aggressive control inputs during the period of disturbance rejection. This case study clearly demonstrates that the MoD-PC effectively rejects the severe disturbance.

2. Setpoint-Tracking Problems

In the operation of continuous polymerization reactors, it is frequently required to produce polymers of different grades. Therfore, the optimization of grade-transition processes has become an important control target. Note that the nonlinear behavior of the polymerization reactors becomes more salient during the grade-transition period than under the steady-state operation.

As an example (Case 3), let us consider a case in which the setpoint for the conversion is increased from 0.1 to 0.15 at 300 min

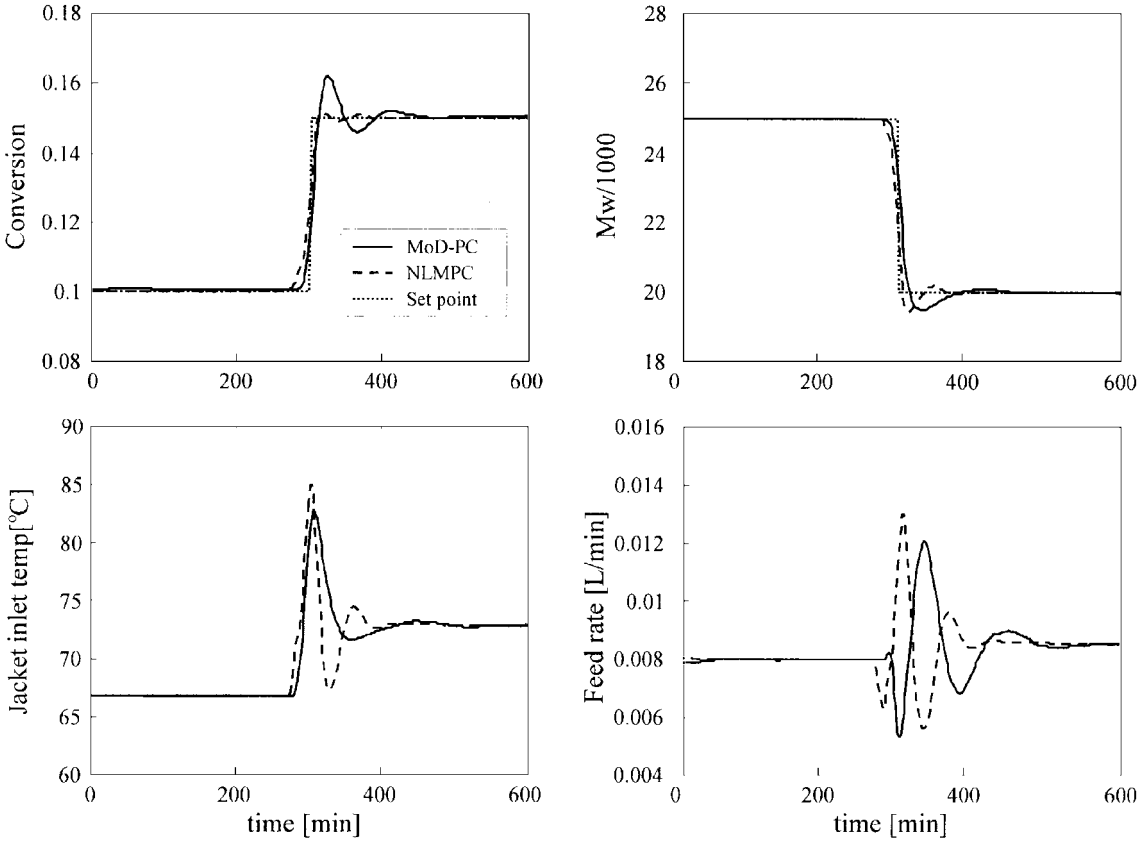

Fig. 4. Setpoint-tracking performances of the MoD-PC and the NLMPC (Case 3).

and the setpoint for the weight-average molecular weight is decreased simultaneously from the 25,000 to 20,000. The setpoint tracking performances are shown in Fig. 4 for both the MoD-PC and the nonlinear MPC.

The MoD-PC produces less aggressive input variations, and this gives rise to a somewhat sluggish response of the outputs when the setpoints change. Though the monomer conversion shows a larger overshoot after the setpoint is changed, the amplitude decays rapidly and the output converges to its new setpoint. It is clearly seen that just before 300 min the jacket inlet temperature jumps up and the feed flow rate drops down to raise the conversion and reduce the weight average molecular weight. Because of the overshoot in the output, the inputs then show the opposite variations. Overall, the control objective is accomplished by a substantial increase in the jacket inlet temperature and a slight increase in the feed flow rate.

Although it produces a somewhat oscillatory behavior, the MoD-PC shows a better response for the average molecular weight than the NLMPC and its overall performance is quite comparable to that of the NLMPC.

3. Noise Attenuation Problems

The algorithm of the MoD-PC is based on the online adaptation of parameters in its local model. In the control algorithm based on the online adaptation, one should evaluate the effect of the measurement noise on the performance of the parameter adaptation since a system hypersensitive to the measurement noise may bring about a biased estimation of parameters. For this purpose, a simulation is conducted in the presence of the measurement noise in both of the controlled outputs under the conditions of Case 1. White noises with zero mean and standard deviation of 0.01 are incorporated in the outputs. As observed in Fig. 5, excessive measurement noises cause larger overshoots and more oscillatory behavior compared to the result in Fig. 2. Though the performance of the MoD-PC is somewhat poorer than that of the nonlinear MPC especially after the disturbance disappeared, both controllers show satisfactory disturbance rejection performance even in the presence of the measurement noise.

CONCLUSIONS

Multivariable MoD-PC is designed to overcome the difficulties associated with a global model identification and on-line optimization that nonlinear MPC may have. The proposed control algorithm is evaluated by applying it to the property control of polymer product in a continuous styrene polymerization reactor. The simulation results for disturbance rejection and setpoint-tracking clearly demonstrate that the MoD-PC shows a satisfactory performance in each case study, which is comparable to that of the nonlinear MPC based on the ARMA model. Considering the additional merits in regard to the optimality and flexibility, one may suggest the MoD-PC as a potential control strategy for the production of polymers with desired properties.

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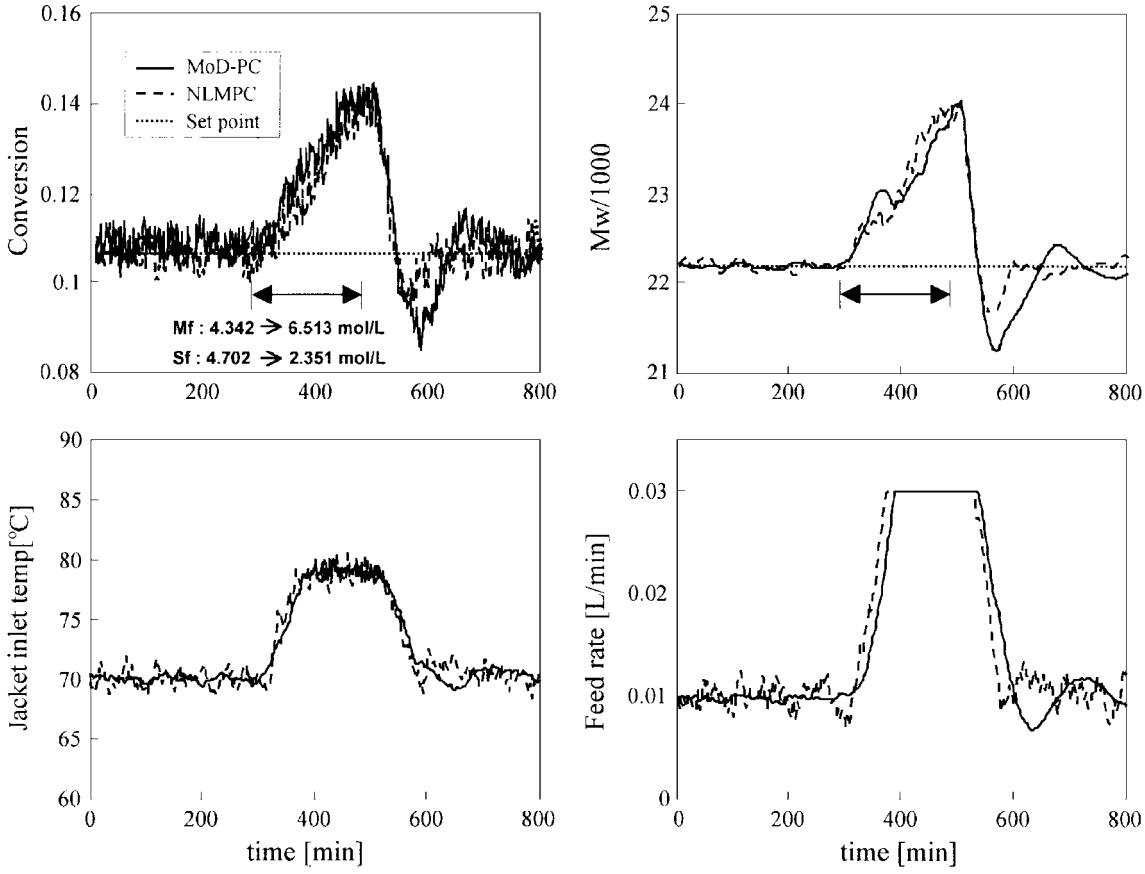

Fig. 5. Regulatory performances of the MoD-PC and the NLMPC in the presence of the measurement noise (Case 1).

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NOMENCLATURE

$\varphi(k)$: regressor states vector at time k
d(x, y): distance between x and y
M : weighting matrix
y(k) : plant output at time k
T_{jin} : jacket inlet temperature
q_f : feed flow rate
X : conversion
Mw : weight-average molecular weight
b : distance criterion
y(k) : output vector
u(k) : input vector
$\hat{\mathbf{y}}(k+p/k)$: p-step ahead output prediction at t=k
$Y_{k+1|k}$: output prediction vector
$R_{k+1/k}$: reference trajectory vector
$\Delta\mathbf{U}_k$: $[\Delta\mathbf{u}(k)^T, L, \Delta\mathbf{u}(k=m-1)^T]^T$
Λ_y : weighting matrix for output, Eq. (10)
$\Lambda_{\Delta u}$: weighting matrix for input, Eq. (10)
p : prediction horizon
m : manipulation horizon

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