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Non-linear model based control of a propylene polymerization reactor

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Abstract

A modified generic model controller is developed and tested through a simulation study. The application involves model-based control of a propylene polymerization reactor in which the monomer conversion and melt index of the produced polymer are controlled by manipulating the reactor cooling water flow and the inlet hydrogen concentration.

Non-linear control is designed using a simplified non-linear model, in order to demonstrate the robustness of the control approach for modeling errors. Two model parameters are updated online in order to ensure that the controlled process outputs and their predicted values track closely. The controller is the static inverse of the process model with setpoints of the measured process outputs converted to setpoints for some of the state variables.

The simulation study shows that the proposed controller has good setpoint tracking and disturbance rejection properties and is superior to the conventional generic model control and Smith predictor control approaches.

Keywords: Non-linear control; Model-based control; Polymerization; Non-linear model; Model parameter update

1. Introduction

Control of polymerization reactors is probably one of the most challenging issues in control engineering. The difficulties in operating such processes are numerous. Firstly, the process dynamics are often highly non-linear because of the complicated reaction mechanisms associated with the large number of interactive reactions. Secondly, on-line monitoring of polymer quality is often hampered by a lack of on-line measurements for key quality variables such as composition (or monomer conversion), molecular weight and copolymer composition [1]. If measuring quality variables is at all possible, there may still be a number of problems associated with these measurements, such as (i) sampling problems, (ii) large dead times, (iii) off-line analysis, and (iv) sometimes large measurement errors and/or high noise levels. A more detailed discussion of measurement difficulties in the field of polymerization can be found, amongst others, in Kiparssides [2]. To cope with the lack of on-line measurements of polymer quality, researchers have employed different inferential and estimation techniques [1,3–5].

Many articles have been published in the area of polymer reactor control in the last few years. They can be divided into linear and non-linear control approaches. There are numerous examples in the literature of linear control approaches applied to polymerization reactor control, such as, PI cascade control [6], dynamic matrix control [7,8], generalized predictive control [9] and adaptive internal model control [10]. Examples of the application of non-linear control approaches are, amongst others, globally linearizing control [11–13] and non-linear model predictive control [14,15]. There are also some approaches in which linear control is used, combined with non-linear models for setpoint updating [16].

Another type of control that has received moderate attention is generic model control (GMC). This method uses a non-linear process model and assuming a desirable process output trajectory, a non-linear control law can be derived. A recent example of its application in combination with extended Kalman filtering is found in Arnpornwichanop et al. [17].

In the current paper an approach similar to generic model control is being proposed, although its implementation and tuning is simpler. It implements the non-linear model of the process directly and gives an on-line estimation for the delayed measurements (Fig. 1); thus, there is no need to design an estimator, such as a Kalman filter. This control strategy is applied to the polymer-

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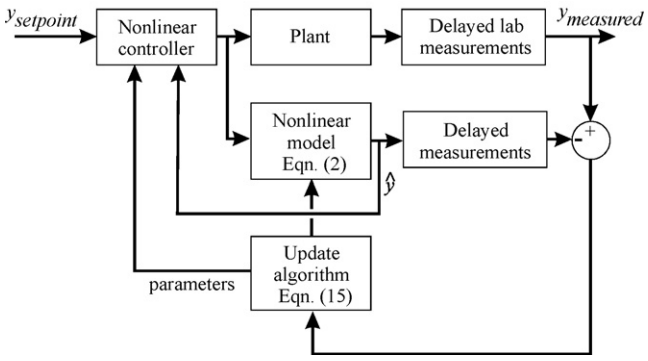

Fig. 1. Reactor control based on simplified non-linear model, using model and controller update.

ization of propylene in a fully-filled hollow shaft reactor [18]. In case of a perfect non-linear model, a perfect non-linear controller can be designed. In case of a simplified non-linear model, the control system is improved by updating two model parameters of the simplified process and control models using an online model parameterization method. The efficiency of this control algorithm is compared to the performance of a conventional PI control system with Smith predictor dead time compensation.

The advantages of the proposed control approach over other approaches are: (i) there is no need for use of an extended Kalman filter to estimate unknown states or parameters, (ii) there is no need to solve the coupled set of non-linear ordinary differential equations, and (iii) the controller shows a good robustness the adaptation of the model parameters, as a result of which errors in dynamics and kinetics can easily be dealt with.

2. Non-linear control

Consider a process, which can be described by the following equations:

$$\frac{dx}{dt} = f(x, p) + g(x, u) + l(x, d)$$
$$y = h(x) \tag{1}$$

where x is the vector of state variables, y the vector of measured variables, u the vector of input variables, d the vector of disturbance variables, p the vector of process parameters, and h, f, g, l are the non-linear function vectors.

Let the model be a simplified description of the process with a different parameter set p and be given by:

$$\frac{d\hat{x}}{dt} = f(\hat{x}, \hat{p}) + g(\hat{x})u + l(\hat{x})d$$
$$\hat{y} = h(\hat{x}) \tag{2}$$

where the hat refers to the model values. In the development of the generic model control algorithm it is assumed that the derivative of y obeys the following equation [19]:

$$\frac{dy}{dt} = K_1(y_{sp} - y) + K_2 \int_0^{t_f} (y_{sp} - y)\, dt \tag{3}$$

were K_1 and K_2 are tuning parameters and y_{sp} is the setpoint value of the process output. Using Eq. (2), the derivative of the state variable can be expressed as:

$$\dot{\hat{x}} = \dot{\hat{y}} \left[\frac{dh(\hat{x})}{d\hat{x}} \right]^{-1} \tag{4}$$

Substitution of the derivative of $\hat{x}$ in Eq. (2) results in:

$$\dot{\hat{y}} \left[\frac{dh(\hat{x})}{d\hat{x}} \right]^{-1} = f(\hat{x}, \hat{p}) + g(\hat{x})u + l(\hat{x})d \tag{5}$$

from which the equation for the control input vector can be derived:

$$u = \left\{ \frac{K_1(y_{sp} - y) + K_2 \int_0^{t_f} (y_{sp} - y)\, dt - (dh/d\hat{x})[f(\hat{x}, \hat{p}) + l(\hat{x})d]}{(dh/d\hat{x})g(\hat{x})} \right\} \tag{6}$$

If the model is not linear in the control vector u, its values have to be computed through iteration. The parameters K_1 and K_2 are tuning parameters. If the model is not perfect, control performance will deteriorate, and the integral action in the controller will eliminate offset. However, it is preferred to use parameter estimation in order to update the model and thus account for parameter and structural errors. Farza et al. [20] suggested a simple non-linear observer, although other estimation schemes are possible, such as, e.g. a Kalman filter.

The tuning parameters K_1 and K_2 enable us to tune such that even some overshoot can be realized. This can primarily be realized through adjustment of K_1. A disadvantage of tuning for some overshoot in one variable is that it also affects the response of the other controlled variables. A smoother response without overshoot will show a smoother response of the other controlled variables.

If parameter update ensures that the model output tracks the true process output, the integral term in Eq. (6) is not required, since there will be no sustained offset in the controlled variables. Hence if $K_2 = 0$ and tuning of K_1 is done very conservatively to suppress variable interaction, one may wonder why one would not use a controller with both tuning values K_1 and K_2 set equal to zero, i.e. use a controller that is based on a static process model with parameter update. This may give a conservative response for setpoint changes, which approaches the open loop response of the system, however, disturbance rejection properties are expected to be good. The controller can then be calculated by the following set of equations:

$$u = \frac{-f(\hat{x}_{sp}, \hat{p}) - l(\hat{x}_{sp}, d)}{g(\hat{x}_{sp})}, \quad \hat{x}_{sp} = h^*(y_{sp}, \hat{x}) \tag{7}$$

where the estimated setpoint values of the output vector could be filtered values of the true setpoint values and the parameter $\hat{p}$ needs to be updated. In Eq. (7) the dimension of the y vector is usually smaller than the dimension of the x vector, therefore not all state variables setpoint values can be calculated, consequently, some setpoint values are set equal to the current values of the state variables from the model. This is also one of the main differences with generic model control where all the state variables follow from the process model and none of them have setpoint targets.