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Active Disturbance Rejection Control of Chemical Processes

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Abstract— **In this paper a novel control strategy, the active disturbance rejection control (ADRC), is applied to the representative process control problems. In the ADRC framework, the disturbance and unmeasured dynamics associated with chemical processes are treated as an additional state variable, which is then estimated and compensated for in real time. This reduces a normally complex, time-varying, nonlinear, and uncertain dynamic process to an approximately linear, time-invariant, cascade-integral form, where a simple proportional-derivative (PD) controller suffices. Simulation studies are performed on two nonlinear continuous stirred tank reactors (CSTR), both demonstrate very good performance in the absence of an accurate mathematical model of the process..**

I. Introduction

Due to the strong global competition, tightening environmental and safety regulations, and the insatiable desire for better product qualities, the operation of chemical processes must continuously move to a higher level of efficiency in order to survive in today's market. Effective control technique is a key to achieve this goal.

Proportional-integral-derivative (PID) controller, a technique that dates back to 1920s, is still the most widely used control technique in process control although the control hardware has already entered the digital era. To overcome the limitations of PID, model based control, such as model predictive control (MPC), has been successfully developed. Plenty of linear MPC applications can be found in various industries. Commercial software is readily available to implement MPC in various industrial control platforms.

Though model based control techniques offer many advantages, there are several potential limitations. First, the performance of model based control techniques is heavily dependent on the availability of an accurate process model. The other issue of model based control comes from the state estimation. A highly accurate model often has a large number of state variables, which causes the difficulty in state estimation due to limited number of measurements. In addition, the newly developed moving horizon estimation techniques just demand a lot of computational effort when using a complicated nonlinear model. Modeling the process and tuning of model based controller are non-trivial tasks. For example, MPC is inherently an optimization problem. Selections of the prediction and control horizons, weights are mainly dependent on designer's experience and trial and error tests, which could be quite expensive. Process control engineers often face the difficulty of designing control system without adequate knowledge of the process dynamics.

Active disturbance rejection control (ADRC) was developed outside the process control area in chemical engineering [1-5]. It has been successfully applied to motion control, aircraft flight control, web tension regulation etc [6-11]. The applications show that, for a number of complex control problems, ADRC results in extremely simple controller design but achieves high performance in tracking and disturbance rejection. The basic idea of ADRC is to use an extended state observer (ESO) to estimate the internal and external disturbances in real time. Then, through disturbance rejection, the originally complex and uncertain plant dynamics is reduced to a simple cascade integral plant, which can be easily controlled by a PD controller. Two important features of ADRC are 1) its lack of dependence of the model; and 2) the excellent disturbance rejection performance. This new control framework, however, has not been applied in process control area yet.

In this paper, the main concept of ADRC is reviewed in Section II. Then ADRC is employed in solving some representative process control problems in Section III and Section IV. The performance of ADRC is compared with PID and the linear MPC. Finally some concluding remarks are given in Section V.

II. Active Disturbance Rejection Control

The active disturbance rejection concept has been applied to problems of different kinds, including single-input single-output (SISO), as well as multi-input multi- output (MIMO), plants that are nonlinear, time-varying, and most of all, uncertain. For illustration purposes, however, the second order motion system is often used, as shown below.

Consider a dynamic system that can be approximated by a second order nonlinear system model structure:

$$\ddot{y} = f(t, y, \dot{y}, w) + bu \tag{2.1}$$

where y is the measured output to be controlled, u is the input, b is a parameter that is roughly known: $b \approx b_0$. The term f represents the combined effect of the internal dynamics and external disturbances w. In practice, an accurate mathematic description of f is often unavailable. ADRC provides a much needed approach to address this problem. The basic idea is: if, somehow, f can be estimated in real time, then it can be canceled using the control signal, which

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reduces (2.1) to a double integral plant. That is, a nonlinear time-varying unknown plant of (2.1) is approximately reduced to a linear time-invariant cascade integral plant, which can be easily controlled using, for example, a PD controller.

It is this ingenious idea that turns a control problem into an estimation one. The proposed solution is described as follows.

A. Extended State Observer

The system (2.1) can be rewritten in the following state space form:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = x_3 + b_0 u \\ \dot{x}_3 = \dot{f} = h \\ y = x_1 \end{cases} \tag{2.2}$$

where the state is augmented with $x_3=f$. Written in a matrix form, it becomes

$$\begin{cases} \dot{x} = Ax + Bu + Eh \\ y = Cx \end{cases} \tag{2.3}$$

where

$$A = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix}, B = \begin{bmatrix} 0 \\ b_0 \\ 0 \end{bmatrix}, E = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}, C = [1 \quad 0 \quad 0].$$

With h unknown, the state observer of (2.3) is

$$\begin{cases} \dot{z} = Az + Bu + L(y - \hat{y}) \\ y = Cz \end{cases} \tag{2.4}$$

where z_1, z_2, z_3 are the estimates of $y, \dot{y}$, and f respectively. This observer is known as the ESO since the state vector in (2.2) is extended to include f and this observer is designed to provide an estimate of that. Note that, properly designed and implemented, the state of the observer (2.4) will track that of the plant (2.3). The parameter vector L can be obtained using, for example, the pole-placement method [4]. For the sake of simplicity, let $\lambda(s) = |sI - (A - LC)| = (s + \omega_o)^3$, we can obtain: $L = [3\omega_o, 3\omega_o^2, \omega_o^3]^T$. The ESO only has two parameters: b_0 and ω_o. The former is usually known to designers; it can also be obtained from open loop response. The latter is a tuning parameter which amounts to the bandwidth of the observer. Adjusting ω_o, the trade-off can be easily made between performance and noise-sensitivity.

B. Controller Design

With $z_3 \approx f$ obtained from the ESO, the following control law

$$u = (u_0 - f)/b_0 \tag{2.5}$$

reduces (2.1) to an approximate double integral plant:

$$\ddot{y} \approx u_0 \tag{2.6}$$

which can be easily controlled using a PD controller of the form:

$$u_0 = k_p(r - z_1) - k_d z_2. \tag{2.7}$$

Clearly, the key idea in ADRC is to estimate f in real time and cancel it in the controller law.

C. First Order Systems

For first order nonlinear system, the controller design is quite similar. Let

$$\dot{y} = f + b_0 u. \tag{2.8}$$

A second order ESO can be designed as

$$\dot{z} = \begin{bmatrix} -2\omega_o & 1 \\ -\omega_o^2 & 0 \end{bmatrix} z + \begin{bmatrix} b_0 & 2\omega_o \\ 0 & \omega_o^2 \end{bmatrix} \begin{bmatrix} u \\ y \end{bmatrix} \tag{2.9}$$

where z_1 tracks y and z_2 tracks f. The controller is

$$u = (u_0 - f)/b_0. \tag{2.10}$$

The plant is now reduced to an integral form and controlled using a proportional controller:

$$\dot{y} = u_0 = k_p(r - z_1). \tag{2.11}$$

III. CASE STUDY 1: A NONLINEAR CONTINUOUS STIRRED TANK REACTOR

Consider a continuous stirred tank reactor (CSTR) example [12] with the governing equations as follows

$$\begin{cases} \dot{x}_1 = -x_1 + Da(1 - x_1)^n \kappa(x_2) \\ \dot{x}_2 = -x_2 + BDa\kappa(x_2)(1 - x_1)^n - \beta(x_2 - x_{2c}) \\ y = x_2 \end{cases} \tag{3.1}$$

where x_1 is the conversion and x_2 the dimensionless temperature; the term $\kappa(x_2) = e^{(\gamma x_2)/(x_2+\gamma)}$ the reaction rate. The parameters are given as: $n = 1$; $Da = 0.017$; $B = 35$; $x_{2c} = 0$; $\beta = 0.2$; $\gamma = 5$. This nonlinear system has three equilibria: $E_{d1} = [0.05, 1.4583]^T$; $E_{d2} = [0.168, 4.90]^T$; and $E_{d3} = [0.226, 6.5917]^T$. E_{d1} and E_{d3} are stable but E_{d2} is unstable [12].

An output feedback control was used to control this reactor [12]. It involves coordinate transforms. Normally an accurate model should be known in order to do the coordinate transform. The system in (3.1) can be considered equivalent to the following system:

$$\begin{aligned} \dot{x} &= f(x) + g(x)u \\ y &= h(x). \end{aligned} \tag{3.2}$$

By taking a coordinate transform $v = \Phi(x)$, the system can be rewritten as follows

$$\begin{cases} \dot{v}_1 = U \\ \dot{v}_2 = q(v_1, v_2) \\ y = v_1. \end{cases} \tag{3.3}$$

Then the actual control signal can be designed as

$$u = \frac{1}{L_g h(x)}(U - L_f h(x)) \tag{3.4}$$

where U is a proportional controller

$$U = -k(v_1 - r). \tag{3.5}$$

This framework is similar to ADRC. However, ADRC does not need a coordinate transform, which may not be easy to find for some systems. Under the ADRC framework, the system can be considered as follows

$$\begin{cases} \dot{x}_2 = f(t) + \beta x_{2c} \\ y = x_2 \end{cases} \tag{3.6}$$

Thus a second order ESO can be applied. The Simulink block diagram for ADRC control of a CSTR is shown in Figure 1. The performance of ADRC is shown in Figure 2-Figure 5, where “C” and “D” represent different initial conditions of temperature and conversion.

Since the setpoint is the open-loop unstable equilibrium, this is not an easy problem. From Figure 2 and Figure 3, it can be seen that ADRC works pretty well, which is comparable to the performance of output feedback control shown in [12]. ADRC does not need an accurate model. However, it can take advantage of certain model information. For example, b is not necessarily to be estimated if the model is accurate. When the model is not perfect, certain biases can be seen in the feedback linearization control. However, these model parameter uncertainties have almost no effect on ADRC since ADRC does not depend on the accuracy of model parameters. In **Error! Reference source not found.** and **Error! Reference source not found.**, it can be seen that ADRC converges to the setpoint with no changes in its performance and output feedback control can not converge to the setpoint.

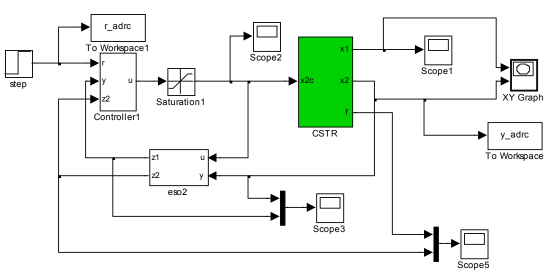

Figure 1 ADRC control of a CSTR.

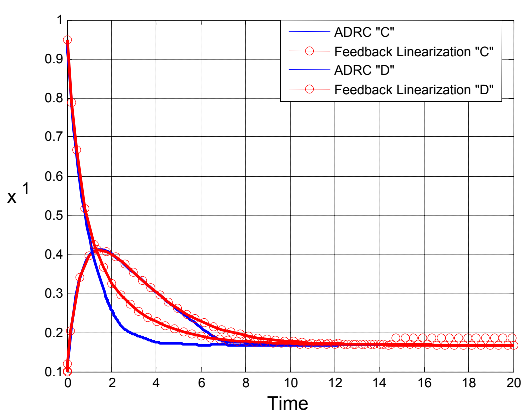

Figure 2 Time history of temperature with an accurate model.

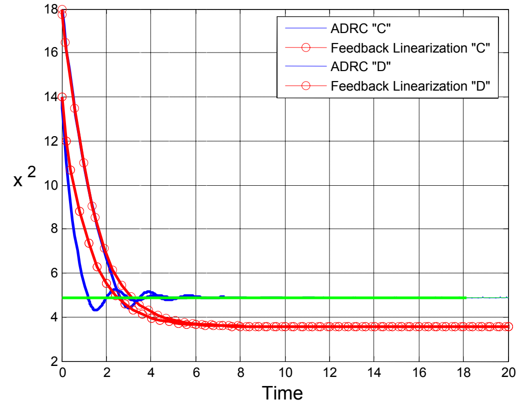

Figure 3 Time history of conversion with an accurate model.

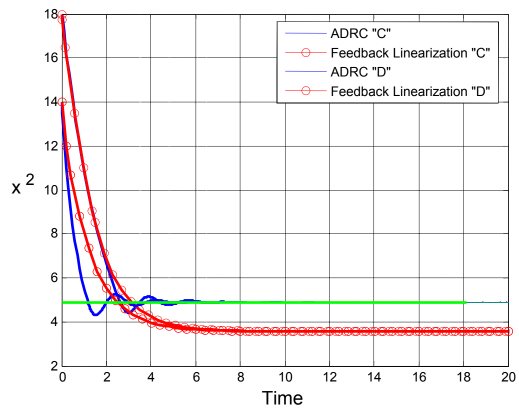

Figure 4 Time history of temperature with 20% error in γ.

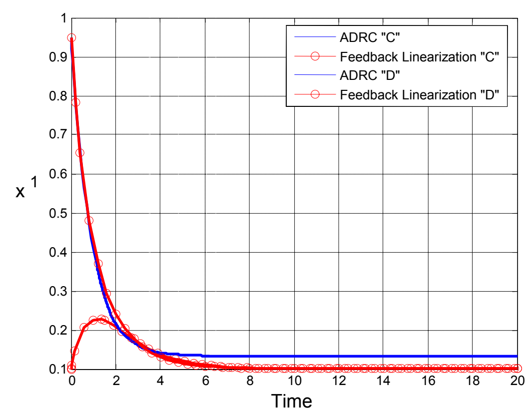

Figure 5 Time history of conversion with 20% error in γ.

IV. CASE STUDY 2: NONLINEAR NON-ISOTHERMAL CSTR WITH TIME-VARYING PARAMETERS

A nonlinear CSTR [13] is shown in Figure 6. Assuming there is an irreversible reaction, $A \rightarrow B$, and the kinetics can be described as $R_A = kC_A$, where k is the reaction constant and $k = k_0 e^{-E_a/RT}$. The CSTR can be modeled as two coupled ordinary differential equations (ODEs), which are obtained from differential mass and energy balances:

$$\frac{dC_A}{dt} = \frac{q}{V}(C_{Af} - C_A) - k_0 C_A \exp\left(-\frac{E}{RT}\right)\phi_c(t) \tag{4.1}$$

$$\frac{dT}{dt}=\frac{q}{V}(T_f-T)+\left(\frac{-\Delta H}{\rho C_p}\right)k_0 C_A \exp\left(-\frac{E}{RT}\right)\phi_c(t) \qquad (4.2)$$
$$+\left(\frac{\rho_c C_{pc}}{\rho C_p V}\right)q_c\left[1-\exp\left(-\frac{hA}{q_c\rho C_{pc}}\phi_h(t)\right)\right]\left(T_{cf}-T\right)$$

where q_c is the manipulated variable; and C_A is the controlled variable. The control mechanism is very complicated. It can be simply stated as follows: the coolant flowrate affects the reactor temperature, and the temperature affects the reaction rate, and the reaction rate determines the product concentration and heat to be generated. In (4.1) and (4.2) $\phi_c(t)$ and $\phi_h(t)$ are time-varying parameters which represent the catalyst deactivation / regeneration and heat transfer fouling. Other parameters are shown in Table 1.

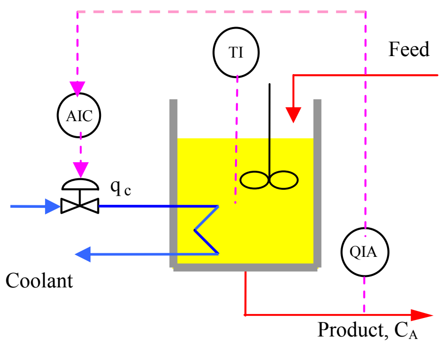

Figure 6 The control scheme of the CSTR example

Table 1 Data of a non-isothermal CSTR

Variable	Value	Unit	Description
Q	100	liter/min	Feed flow rate
C_{Af}	1	mol/liter	Feed Concentration
T_f	350	K	Feed temperature
V	100	liter	Volume of reactor
hA	7×10^5	cal/min/k	Heat transfer coefficients
k_0	7.2×10^{10}	min^{-1}	Rate constant
E/R	9.95×10^3	K	Activation energy
Q_c	103.4	l/min	Coolant flow-rate
ρ,ρ_c	1000	g/l	Density
$-\Delta H$	2×10^5	cal/mol	Heat of reaction
C_p, C_{pc}	1	$cal.g^{-1}.K^{-1}$	Heat Capacity
T	440.2	K	Temperature
C_A	0.0836	mol/liter	Outlet concentration

The system of two first order equations is equivalent to a second order nonlinear system. As the time varying parameters $\phi_c(t)$ and $\phi_h(t)$ are generally unknown, we can assume both equal to 1 for simplification purpose for the time being. From (4.1), we have

$$T=\frac{\left(\frac{E}{R}\right)}{\ln\left[k_0C_A\right]-\ln\left[\frac{q}{V}(C_{Af}-C_A)-\frac{dC_A}{dt}\right]} = f_1\left(C_A,\frac{dC_A}{dt}\right). \qquad (4.3)$$

Differentiating both sides of (4.1), we have

$$\frac{d^2C_A}{dt^2}=-\frac{q}{V}\frac{dC_A}{dt}-k_0\frac{dC_A}{dt}\exp\left(-\frac{E}{RT}\right) -k_0C_A\exp\left(-\frac{E}{RT}\right)\left(\frac{E}{RT^2}\right)\frac{dT}{dt}. \qquad (4.4)$$

Substituting (4.2) into (4.4), it follows that

$$\frac{d^2C_A}{dt^2}=-\frac{q}{V}\frac{dC_A}{dt}-k_0\frac{dC_A}{dt}\exp\left(-\frac{E}{RT}\right) -k_0C_A\exp\left(-\frac{E}{RT}\right)\left(\frac{E}{RT^2}\right) \qquad (4.5)$$
$$\left\{\frac{q}{V}(T_f-T)+\left(\frac{-\Delta H}{\rho C_p}\right)k_0C_A\exp\left(-\frac{E}{RT}\right) +\left(\frac{\rho_cC_{pc}}{\rho C_pV}\right)q_c\left[1-\exp\left(-\frac{hA}{q_c\rho C_{pc}}\right)\right]\left(T_{cf}-T\right)\right\}.$$

Defining

$$\begin{cases} y=C_A \\ f_1(y,\dot y)=T \\ f_2(y,\dot y)=-\frac{E}{RT^2} \\ f_3(y,\dot y)=\exp(-\frac{E}{RT}). \end{cases} \qquad (4.6)$$

then we have

$$\ddot y=\underbrace{k_1\dot y+k_2\dot y f_3+k_3yf_2f_3+k_4yf_1f_2f_3+k_5y^2f_2f_3^2}_{f(y,\dot y,w,t)} +u\underbrace{(1-g(u))(k_6y_1f_1f_2-k_7y_1f_1^2f_2)}_{b}. \qquad (4.7)$$

Comparing this equation with the standard form of ADRC, we have

$$\ddot y=f(y,\dot y,w,t)+bu. \qquad (4.8)$$

It can be seen that in principle CSTR can be controlled using ADRC. In (4.7), b is a function of $y,\dot y$, and t and can be estimated. Since ADRC is very robust, one can see that even a constant estimate b_0 works very well.

The controller design is straightforward. First, an ESO is designed and tuned to make sure it estimates the system states well. Then, a PD controller is designed and tuned to achieve good tracking performance. The tuning parameters are ω_o and ω_c.

A. Constant Parameters

First, let us take a look at a simple case by assuming time varying parameters are constant, i.e., $\phi_c(t)=1$ and $\phi_h(t)=1$. Figure 7 shows the open loop responses for different step inputs. The system shows strong nonlinearities. When the input is increased by +10%, one can see that system has damping oscillations. In this example, the setpoint is the desired composition of the product, which can also be referred to the product purity.

One important feature is that the product purity may change from time to time due to variations of customer requirement, price/cost or other economic factors. Thus, the setpoint tracking performance is a very important index to evaluate the control system design. The disturbance rejection performance is another very important index to evaluate control system design. In general, a chemical process consists of many units. Upset in upstream process can cause disturbances to the downstream process. The raw material which is fed into the reactor is usually a product of the other process. Thus, the feed flow rate is subject to fluctuation due to the upstream process disturbance.

To evaluate the control system performance and robustness, both setpoint tracking and disturbance rejection

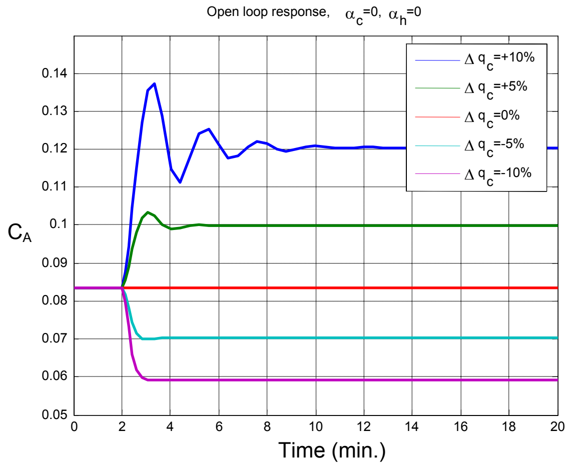

Figure 7 The open-loop response of the CSTR with constant parameters.

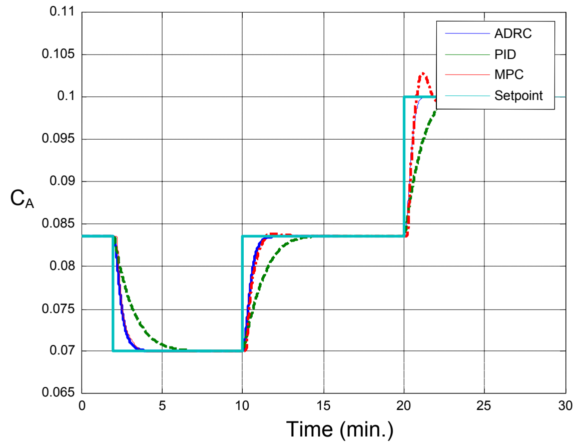

Figure 8 The setpoint tracking performance of the CSTR with constant parameters.

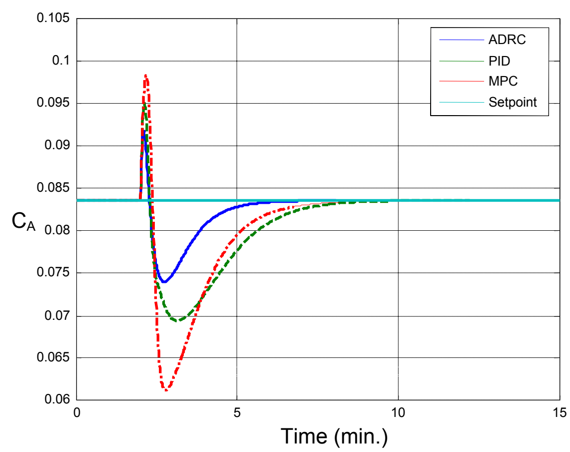

Figure 9 The disturbance rejection performance for +20% change in the feed flow rate of the CSTR with constant parameters.

performance are investigated. To illustrate the advantages of ADRC, it is compared to PID and MPC. As most industrial MPC algorithm employs linear model, linear MPC is applied here. The nonlinear CSTR is linearized at the normal operation point. Figure 8 shows the setpoint tracking performance. From Figure 8, we can observe that ADRC tracks the setpoint change very well; PID is much slower; and MPC shows some overshoots when the setpoint is raised. The main reason is the model/plant mismatch due to the strong nonlinearities of CSTR. Figure 9 shows the disturbance rejection performance. For 20% change in inlet flow rate as disturbance, one can easily see that ADRC is superior to MPC or PID.

B. Time-varying Heat Transfer Coefficient

The model is usually an approximation of the real process. For the CSTR, reaction generates heat and heat need be removed by the cooling water. Fouling occurs when the material is deposited on a heat transfer surface during the period of process operation. This will increase the resistance of heat transfer. In general, this fouling process cannot be modeled accurately. Linear fouling can be assumed $\phi_c(t)=1$ and $\phi_h(t)=1-0.01t$.

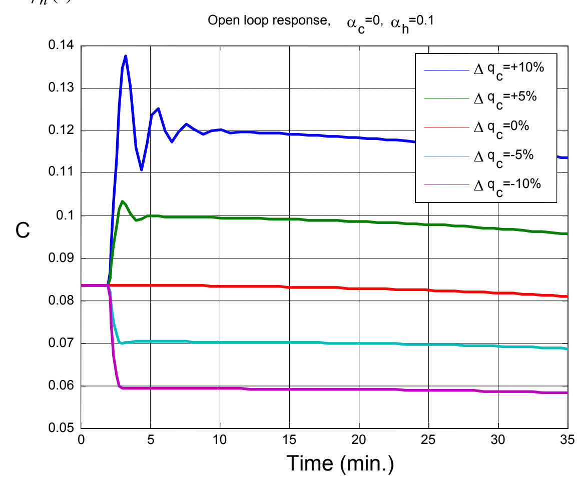

Figure 10 The open-loop response of the CSTR with time-varying heat transfer coefficient.

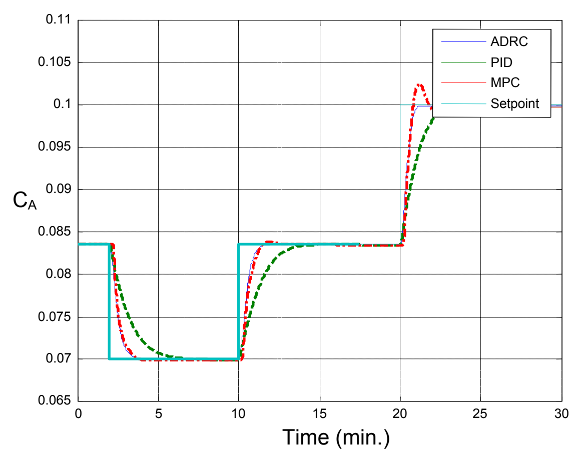

Figure 11 The setpoint tracking performance of the CSTR with time-varying heat transfer coefficient.

The open-loop response, setpoint tracking performance, and disturbance rejection performance are shown in Figure 10, Figure 11, and Figure 12 respectively. The open-loop response shows the system will drift away when the fouling is considered. As fouling is a slow process, the setpoint tracking and disturbance rejection performance remain the same.

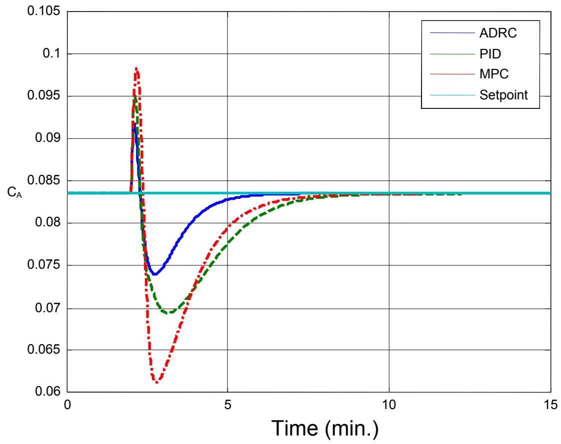

Figure 12 The disturbance rejection performance for +20% change in the feed flow rate of the CSTR with time-varying heat transfer coefficient.

C. Time Varying Activation Energy

$$\phi_c(t) = \exp(-\frac{0.0067}{2}\frac{E}{RT}t) \text{ and } \phi_h(t) = 1 - 0.01t$$

When the catalyst is present, the reaction rate is greatly affected by the condition of the catalyst. During the period of operation, the catalyst may be deactivated due to poisoning. An empirical correlation can be used just for the simulation purpose because sometimes the catalyst deactivation is unpredictable. The open-loop response, the setpoint tracking performance, and the disturbance rejection performance are shown in Figure 13 - Figure 15 respectively. From the open-loop response, one can see that the system becomes highly unstable. As the catalyst becomes highly deactivated, the reaction is nearly shut down and the product concentration approaches to the feed concentration. We can see that the performance of ADRC is much better than that of MPC and PID. MPC starts oscillating severely because of the large prediction error caused by plant/model mismatch.

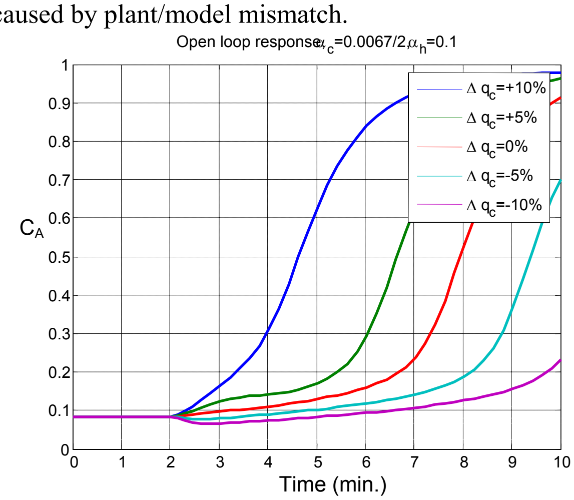

Figure 13 The open-loop response of the CSTR with time-varying activation energy (Case Study 2.C).

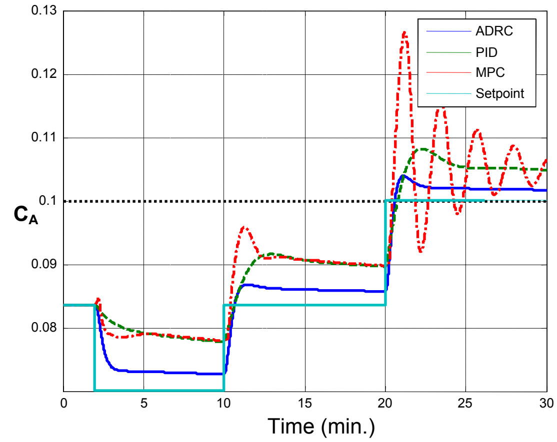

Figure 14 The setpoint tracking performance of the CSTR with time-varying activation energy (Case Study 2.C).

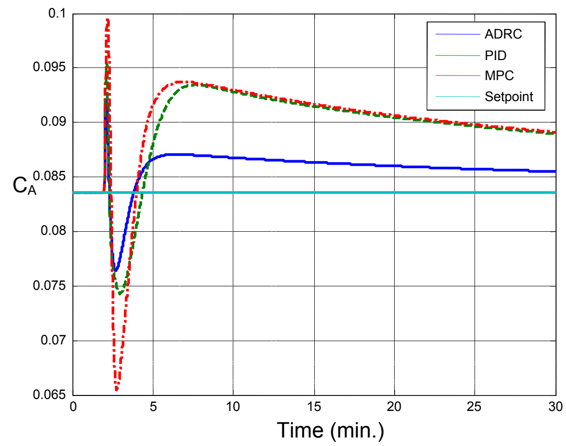

Figure 15 The disturbance rejection performance for +20% change in the feed flow rate of the CSTR with time-varying activation energy (Case Study 2.C).

D: Time-varying Activation Energy

$$\phi_c(t) = \exp(\frac{0.0067}{2}\frac{E}{RT}t) \text{ and } \phi_h(t) = 1 - 0.01t$$

In this paper, we consider an interesting case when the catalyst is regenerated. During this process, the catalyst is reactivated and the reaction rate can become very large. This is a very dangerous situation. A lot of heat is generated but it can not be removed in time. This could cause the reactor to lose control and equipment damage. Sometimes an explosion may cause severe injury. The open-loop simulation shown in Figure 16 clearly demonstrates this point. The setpoint tracking performance and the disturbance rejection performance are shown in Figure 17 and Figure 18 respectively. The closed-loop simulation shows that the performance of ADRC is much better than that of PID and MPC without retuning controller or ESO parameters.

Note that in the above simulations, b is estimated as a constant. As b is a function, it can be estimated more accurately using piece-wise function according to different operating condition, thus, better performance can be expected. For MPC, a nonlinear MPC might perform better. However, as the time varying parameters are present and it is not clear that how these parameters change, nonlinear MPC still has the model/plant mismatch problem and it does not necessarily perform better.

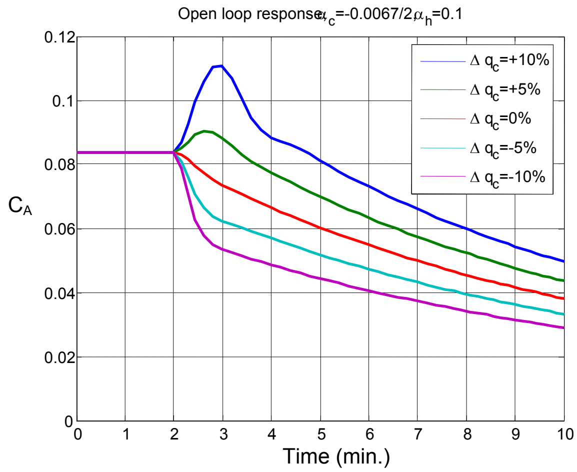

Figure 16 The open-loop response of the CSTR with time-varying activation energy (Case Study 2.D).

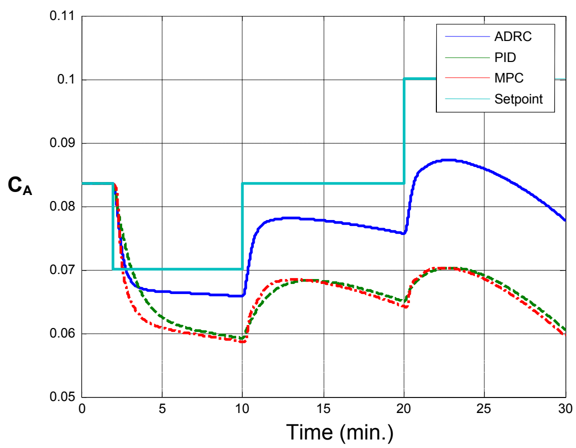

Figure 17 The setpoint tracking performance of the CSTR with time-varying activation energy (Case Study 2.D).

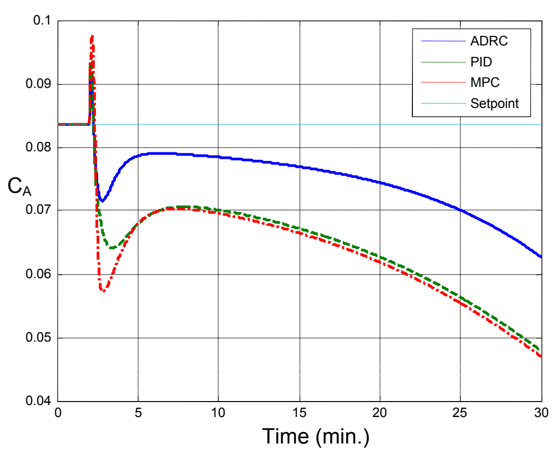

Figure 18 The disturbance rejection performance for +20% change in the feed flow rate of the CSTR with time-varying activation energy (Case Study 2.D).

V. CONCLUDING REMARKS

The novel active disturbance rejection design concept proves to be quite effective in dealing with unique characteristics of process control problems, as demonstrated in two case studies in the paper. In the ADRC framework, the disturbance and un-modeled dynamics are treated as an extra state variable and estimated using a state observer. Using this additional information in a unique disturbance rejection scheme, the resulting control design becomes quite straightforward, as the plant is reduced to a simple cascade integral form.

Two representative process control problems are discussed, which include a strong nonlinear non-isothermal CSTR. The ADRC design methodology proves to be a powerful technique, especially in the disturbance rejection. Design and tuning are much simpler compared to MPC. More importantly, ADRC does not require detailed knowledge of the process dynamics. It appears to be a promising approach in solving certain process control problems in which an accurate model is difficult to obtain.

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