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A Dynamic Decoupling Control Approach and Its Applications to Chemical Processes

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Abstract—**In this paper, a unique dynamic decoupling control strategy, based on the active disturbance rejection control framework, is proposed for square multivariable systems. With the proposed method, it is shown that a largely unknown square multivariable system is readily decoupled by actively estimating and rejecting the effects of both the internal plant dynamics and external disturbances. By requiring as little information on plant model as possible, the intention is to make the new method practical. Simulation results obtained on two chemical process problems show good performance in the presence of significant unknown disturbances and unmodeled dynamics.**

I. INTRODUCTION

MULTI-input multi-output (MIMO) systems, also known as multivariable systems, permeate industry. The interactions or cross-couplings among various inputs and outputs of a system make design technologies in multivariable control systems fundamentally different from single-input single-output (SISO) control systems. Given that our understanding of the physics of MIMO systems usually helps us identify the dominant input-output pairs, one design strategy is to disentangle the interactions among various input-output pairs and reduce a multivariable system into a number of independent SISO systems. This strategy is known as decoupling. Granted such a strategy is not the only one, but it is a method of choice in some sectors in industry, such as chemical processes.

Decoupling of linear time invariant (LTI) multivariable systems has drawn researchers' interest in the past several decades [1-7], making it a well established area. The premise, however, is that the system is well represented by a LTI model. Robustness, disturbance rejection, and other practical concerns continue to pose serious challenges [1]. It is well known that the attenuation of load disturbances is of a primary concern in control system design [8], particularly for process control [9]. In fact, the countermeasure of disturbances is one of the key factors for successful or failed applications [10]. In conjunction with decoupling control, the importance of disturbance rejection has been recognized by many researchers. One class of disturbance rejection methods for decoupling control is based on the concept of the disturbance observer [11-16], but the effectiveness of the existing disturbance rejection methods is limited by the requirement of an accurate mathematical model of the plant. In engineering practice, however, such presumption is hardly warranted as many industrial processes are highly uncertain and are in a perpetual flux.

In this paper, a novel disturbance rejection based decoupling control approach is proposed. Unlike many existing decoupling methods, the new method requires very little information of the plant dynamics. This decoupling control method is rooted in a recently proposed novel control method: active disturbance rejection control (ADRC). The original concept of active disturbance rejection was proposed by J. Han [17-19]. Although the idea is quite imaginative, the nonlinear structure and a large number of tuning parameters, which need to be manually adjusted in implementation, make its large scale practical applications challenging. Recently, a new parameterization and tuning method was proposed, which greatly simplified the implementation of ADRC and made the design transparent to practicing engineers [20, 21]. More importantly, with the proposed parameterization of ADRC, it becomes a viable candidate for decoupling control.

ADRC is a quite different design philosophy. At its foundation is the recognition that, in the real world, dynamic systems are often highly uncertain, both in terms of the internal dynamics and external disturbances. The magnitude of the uncertainties could make them well beyond the reach of prevailing robust control theories, such as H_2/H_∞. ADRC offers a solution where the necessary modeling information needed for the feedback control system to function well is obtained through the input-output data of the plant in real time. Consequently, the control system can react promptly to the changes either in the internal dynamics of the plant, or its external disturbances. As first shown in [22] for aircraft flight control and then in [23] for the jet engine problem, ADRC is a natural solution to decoupling control problems in the presence of large uncertainties. Compared to the above problems, the dynamics of some industrial systems, such as chemical processes, is even more nonlinear with less information available on how each input affects various outputs, which is needed to be known in the method used in [22, 23]. To address such challenges, a dynamic decoupling control (DDC) approach is proposed in this paper. With little modeling information assumed, namely the predetermined input-output paring, the decoupling problem is reformulated as that of disturbance

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rejection, where disturbance is defined as the cross channel interference. The effect of one input to all other outputs that it is not paired with is viewed as a disturbance to be rejected. In the ADRC framework, such disturbance is actively estimated using the extended state observer (ESO) and canceled in the control law, in the absence of an accurate mathematical model of the plant.

The paper is organized as follows. It is shown how a decoupling problem can be reformulated and solved as a disturbance rejection problem in Section II. Two case studies of chemical problems are performed on linear and nonlinear multivariable systems in Section III. Finally, some concluding remarks are given in Section IV.

II. A Disturbance Rejection Based Dynamic Decoupling Control Method

ADRC is a relatively new control design concept. In this paper, ADRC based DDC approach is proposed to address the decoupling problem for systems with large uncertainties of the internal dynamics and significant unknown external disturbances. Let

$$\begin{aligned} \vartheta_1 &= \left[y_1^{(n_1-1)}(t), y_1^{(n_1-2)}(t), \cdots, y_1(t)\right], \\ \vartheta_2 &= \left[y_2^{(n_2-1)}(t), y_2^{(n_2-2)}(t), \cdots, y_2(t)\right], \\ &\vdots \\ \vartheta_m &= \left[y_m^{(n_m-1)}(t), y_m^{(n_m-2)}(t), \cdots, y_m(t)\right], \\ u &= \left[u_1(t), u_2(t), \cdots, u_m(t)\right]. \end{aligned} \tag{1}$$

Consider a system formed by a set of coupled input-output equations with predetermined input-output parings

$$\begin{cases} y_1^{(n_1)} = p_1(\vartheta_1, \vartheta_2, \cdots, \vartheta_m, u, w_1) + b_{11}u_1 \\ y_2^{(n_2)} = p_2(\vartheta_1, \vartheta_2, \cdots, \vartheta_m, u, w_2) + b_{22}u_2 \\ \quad \vdots \\ y_m^{(n_m)} = p_m(\vartheta_1, \vartheta_2, \cdots, \vartheta_m, u, w_m) + b_{mm}u_m \end{cases} \tag{2}$$

where y_i is the output, u_i is the input, w_i is the external disturbances of the i^{th} loop, respectively, and $y_i^{(n_i)}$ denotes the n_i^{th} order derivative of y_i, $i = 1, 2, \cdots, m.$ Note that i refers to $i = 1, 2, \cdots, m$ in the following. In (2), we assume that the numbers of inputs and outputs are the same; the orders n_i and the approximate values of b_{ii} are given. Define

$$f_i = p_i(\vartheta_1, \vartheta_2, \cdots, \vartheta_m, u, w_i) + (b_{ii} - b_{0,ii})u_i \tag{3}$$

where $b_{0,ii}$ is the approximate value of b_{ii}, and f_i represents the combined effect of internal dynamics and external disturbances in the i^{th} loop, including the cross channel interference. Then (2) can be written as

$$\begin{cases} y_1^{(n_1)} = f_1 + b_{0,11}u_1 \\ y_2^{(n_2)} = f_2 + b_{0,22}u_2 \\ \quad \vdots \\ y_m^{(n_m)} = f_m + b_{0,mm}u_m. \end{cases} \tag{4}$$

A presumption in most existing decoupling control approaches is that an accurate mathematical model of the plant has been obtained. This could pose some rather considerable challenges time and cost wise in engineering practice. This is where the ADRC concept comes in. The idea is: if there is a viable alternative that allows us to realistically estimate f_i in real time from input-output data, then the accurate mathematical description of f_i might not be required. It is the aim of this paper to establish that ESO is indeed a suitable solution for this task.

The square multivariable system (4) is an $m-$loop system. An ADRC based SISO controller is designed for each loop independently. Consider the i^{th} loop in (4)

$$y_i^{(n_i)} = f_i + b_{0,ii}u_i. \tag{5}$$

Let $x_{1,i} = y_i, x_{2,i} = \dot{y}_i, \cdots, x_{n_i,i} = y_i^{(n_i-1)}$ and $x_{n_i+1,i} = f_i$, which is added as an extended state. Assume f_i is differentiable and $h_i = \dot{f}_i$ is bounded. The augmented state space form of (5) is

$$\begin{cases} \dot{x}_i = Ax_i + Bu_i + Eh_i \\ y_i = Cx_i \end{cases} \tag{6}$$

where

$$A = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \cdots & \cdots & \cdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \\ 0 & 0 & 0 & \cdots & 0 \end{bmatrix}_{(n+1)\times(n+1)}, \quad B = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ b_{0,ii} \\ 0 \end{bmatrix}_{(n+1)\times 1}, \quad E = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix}_{(n+1)\times 1},$$

$$C = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \end{bmatrix}_{1\times(n+1)}.$$

An ESO for (6) is designed as

$$\begin{cases} \dot{\hat{x}}_i = A\hat{x}_i + Bu_i + L_i(x_{1,i} - \hat{x}_{1,i}) \\ \hat{y}_i = C\hat{x}_{1,i} \end{cases} \tag{7}$$

where $L_i = \left[l_{1,i}.l_{2,i}, \cdots, l_{n_i,i}, l_{n_i+1,i}\right]^T$ is the observer gain. In particular, let us consider a special case where the gains are chosen as

$$\left[l_{1,i}.l_{2,i}, \cdots, l_{n_i,i}, l_{n_i+1,i}\right]^T = \left[\omega_{o,i}\alpha_{1,i}, \omega_{o,i}^2\alpha_{2,i}, \cdots, \omega_{o,i}^{n_i+1}\alpha_{n_i+1,i}\right]^T \tag{8}$$

with $\omega_{o,i} > 0$. Here $\alpha_{j,i}, j = 1, 2, \cdots, n_i + 1$ are chosen such that $s^{n_i+1} + \alpha_{1,i}s^{n_i} + \cdots + \alpha_{n_i,i}s + \alpha_{n_i+1,i}$ is Hurwitz. For simplicity, we just let $s^{n_i+1} + \alpha_{1,i}s^{n_i} + \cdots + \alpha_{n_i,i}s + \alpha_{n_i+1,i} = (s+1)^{n_i+1}$ where $\alpha_{j,i} = \dfrac{(n_i+1)!}{j!(n_i+1-j)!}$, $j = 1, 2, \cdots, n_i + 1$. It results in the characteristic polynomial of (7) to be

$$\lambda_{o,i}(s) = s^{n_i+1} + \omega_{o,i}\alpha_{1,i}s^{n_i} + \cdots + \omega_{o,i}^{n_i}\alpha_{n_i,i}s + \omega_{o,i}^{n_i+1}\alpha_{n_i+1,i} = (s + \omega_{o,i})^{n_i+1}. \tag{9}$$

This makes $\omega_{o,i}$, which is the observer bandwidth of the i^{th} loop, the only tuning parameter for the i^{th} loop observer and the implementation process much simplified, compared to other observers.

With a well-tuned observer, the observer states will closely track the states of the augmented plant. By canceling the effect of f_i using $\hat{f}_i$, ADRC actively compensates for

f_i in real time. The control law of the i^{th} loop is designed as follows. First, the control law

$$u_i = \frac{u_{0,i} - \hat{f}_i}{b_{0,ii}} \tag{10}$$

approximately reduces the original plant (5) to

$$y_i^{(n_i)} \approx u_{0,i} \tag{11}$$

which is a much simple control problem to deal with. The control law is given by

$$u_i = k_{1,i}(r_i - \hat{x}_{1,i}) + \cdots + k_{n_i,i}(r_i^{(n_i-1)} - \hat{x}_{n_i,i}) + r_i^{(n_i)} \tag{12}$$

where r_i is the desired trajectory of the i^{th} loop. Note that a feedforward mechanism is employed in (12) to further reduce the tracking error. The controller gains are selected so that the closed-loop characteristic polynomial $s^{n_i} + k_{n_i,i}s^{n_i-1} + \cdots + k_{1,i}$ is Hurwitz. To further reduce the tuning parameters, all the controller poles are placed at $-\omega_{c,i}$. Then the approximate closed-loop characteristic polynomial becomes

$$\lambda_{c,i}(s) = s^{n_i} + k_{n_i,i}s^{n_i-1} + \cdots + k_{1,i} = (s + \omega_{c,i})^{n_i} \tag{13}$$

where $k_{j,i} = \frac{n_i!}{(j-1)!(n_i-j+1)!}\omega_{c,i}^{n_i-j+1}, j = 1,2,\cdots,n_i$. This makes $\omega_{c,i}$, which is the controller bandwidth, the only tuning parameter for the i^{th} loop controller.

In summary, the proposed DDC approach, as shown above, renders a new alternative for decoupling control problems. With the convergence of ESO and the stability analysis of ADRC shown elsewhere [30, 31], the chief contribution of this paper is to show that the decoupling problems can be reformulated as a disturbance rejection one, without an elaborate plant model. In fact, the only information required is the orders of the subsystems associated with each input-output pair and the approximate values of the corresponding input gains b_{ii}. Even when b_{ii} are unknown, the DDC method can still be implemented with $b_{0,ii}$ as the tuning parameters [24-26]. Being able to deal with multivariable systems that have different orders for different input-output parings is another advantage of the proposed method. Overall, the DDC is a conceptually simple and easy to understand, and above all, practical solution for real world decoupling problems, where there is a large amount of uncertainties.

III. Case Studies

A. A Linear Multivariable System

A square multivariable system with two inputs and two outputs is illustrated how a linear MIMO system can be controlled by the proposed DDC framework. Distillation columns are very commonly used separation equipment in chemical and process industries. Fig. 1 shows a simplified scheme of distillation column. A stream of mixture enters the column in the middle and two products exit. The light product is drawn from the top and the heavy product is obtained from the bottom. The objective of the controller is to keep the purity of light product y_1 and the purity of heavy product y_2 at their desired values by manipulating the reflux flow rate u_1 and steam flow rate u_2. Generally, the feed flow rate is fixed. In case that the upstream process changes, the feed flow rate may have a disturbance.

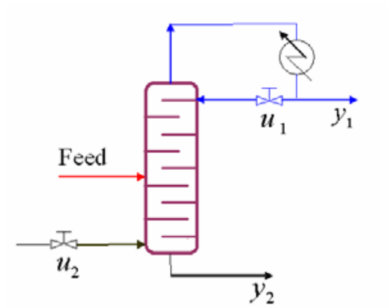

Fig. 1 A simplified scheme of distillation column.

In this paper, we consider the Wood-Berry model of a pilot-scale distillation column [27] with delay set to zero, which is shown as below:

$$\begin{bmatrix} y_1(s) \\ y_2(s) \end{bmatrix} = \begin{bmatrix} \frac{K_{11}}{T_{11}s+1} & \frac{K_{12}}{T_{12}s+1} \\ \frac{K_{21}}{T_{21}s+1} & \frac{K_{22}}{T_{22}s+1} \end{bmatrix} \begin{bmatrix} u_1(s) \\ u_2(s) \end{bmatrix} \tag{14}$$

where $K_{11} = 12.8, K_{12} = -18.9, K_{21} = 6.6, K_{22} = -19.4; T_{11} =$ 16.7, $T_{12} = 21$, $T_{21} = 10.9$, $T_{22} = 14.4$. The system (14) can be represented as

$$\begin{cases} \dot{y}_1(t) = f_1 + \frac{K_{11}}{T_{11}T_{12}}u_1(t) \\ \dot{y}_2(t) = f_2 + \frac{K_{22}}{T_{21}T_{22}}u_2(t) \end{cases} \tag{15}$$

which is the form of (4). Note f_1 and f_2 account for all other factors except u_1 and u_2 in loop 1 and loop 2 respectively.

1) Setpoint Tracking and Disturbance Rejection Performance

Let setpoints: $r_1 = 0,\ r_2 = 1$. We add unmeasured disturbances into the system as follows:

$$t = 0, d = 0; t = 50,\ D(s) = \begin{bmatrix} \frac{K_{d1}}{T_{d1}s+1} \\ \frac{K_{d2}}{T_{d2}s+1} \end{bmatrix} d, t = 100,\ d = 0.$$

where $K_{d1} = 3.8,\ K_{12} = 4.9; T_{d1} = 14.9,\ T_{d2} = 13.2; d =$ 0.735. The comparisons of disturbance rejection performance between the proposed DDC approach and MPC for Loop 1 and Loop 2 of the distillation column are shown in Fig. 2 and Fig. 3 respectively. Their respective design or tuning parameters are as below. DDC parameters: $\omega_{c1} = \omega_{c2} = 0.2; \omega_{o1} = \omega_{o2} = 3; b_{0,11} = 0.8, b_{0,22} = -1.4$. MPC parameters: model horizon: 120, sampling rate: 1min, prediction horizon: 90, control move horizon: 30, output weightings: [1 1], and control weightings: [0.1, 0.1]. Fig. 2 and Fig. 3 show that the DDC achieves better performance than MPC in disturbance rejection.

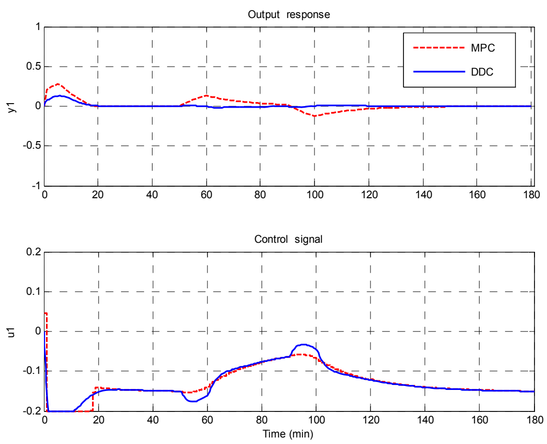

Fig. 2 The comparison of disturbance rejection performance between DDC and MPC for Loop 1 of the distillation column.

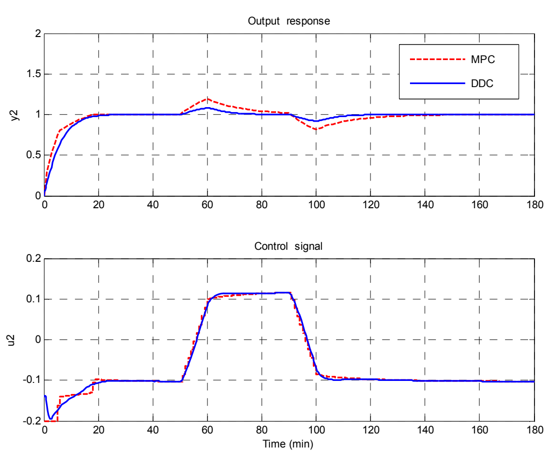

Fig. 3 The comparison of disturbance rejection performance between DDC and MPC for Loop 2 of the distillation column.

2) Control Signal Selection

In practice, it is difficult to decide which control signal should be chosen for one specific loop in the absence of the plant model information. With the proposed DDC approach, this turns out not to be a problem. Consider the system

$$\begin{cases} \dot{y}_1 = f_1 + b_{11}u_1 + b_{12}u_2 \\ \dot{y}_2 = f_2 + b_{21}u_1 + b_{22}u_2 \end{cases} \tag{16}$$

With $b_{12} = 5b_{11}, b_{21} = 5b_{22}$, u_1 is the control signal of loop1, and u_2 is the control signal of loop2. The output performance and control signal with DDC are shown in Fig. 4. The simulation result demonstrates that DDC can control the system well when non-dominant control signals are chosen to control each loop respectively.

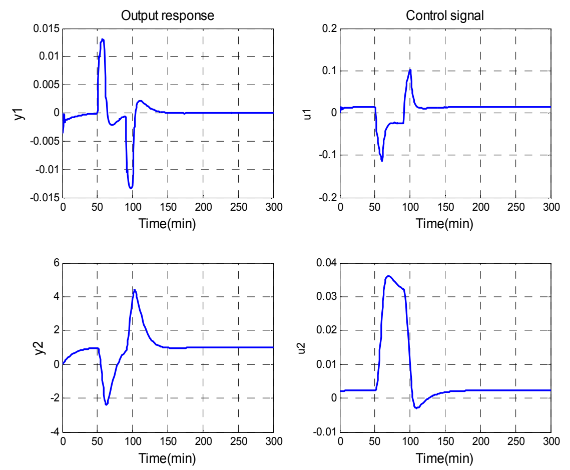

Fig. 4 The performance with non-dominant control signal selection for each loop.

B. A Nonlinear Multivariable System

The continuous stirred tank reactor (CSTR) is widely used in chemical and process industries. Due to its highly nonlinear nature, it is a very important benchmark problem in process control. The system studied here is a CSTR with an irreversible exothermic first order reaction $A \to B$, which exhibits highly nonlinear characteristics [28]. Fig. 5 shows the CSTR diagram. A pure stream of species A enters a constant volume reactor and a well-mixed stream of species A and B exit the reactor. The control objective is to keep the reactor concentration C_A and the reactor temperature T at their desired settings. The manipulated variables are the reactant feed flow rate F_{in} and the coolant water mass rate at the inlet F_w.

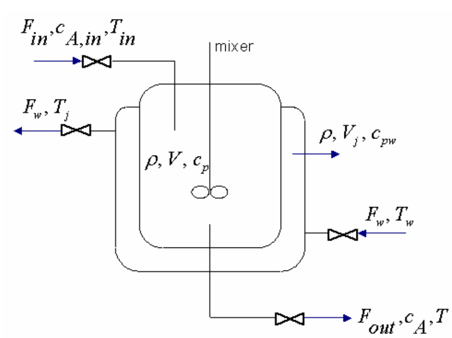

Fig. 5 The CSTR diagram [29].

According to the reactant mass balance, reactor energy balance and the cooling jacket energy balance, a dynamic model of the plant is obtained. The plant model can be written into a standard nonlinear system representation as the following [29]:

$$\dot{x}=\begin{bmatrix} -rx_1 \\ \dfrac{-V\triangle Hrx_1+UA(x_3-x_2)}{V\rho C_p} \\ \dfrac{UA(x_2-x_3)}{V_j\rho_w C_{pw}} \end{bmatrix}+\begin{bmatrix} \dfrac{C_{A,in}-x_1}{V} & 0 \\ \dfrac{T_{in}-x_2}{V} & 0 \\ 0 & \dfrac{T_w-x_3}{V_j\rho_w} \end{bmatrix}u \qquad (17)$$

$$\begin{bmatrix} y_1 & y_2 \end{bmatrix}^T=\begin{bmatrix} \dfrac{C_{A,in}-x_1}{C_{A,in}} & x_2 \end{bmatrix}^T$$

where

$$r=k_0\exp(\frac{-E}{Rx_2})$$

$$x=\left[x_1,\,x_2,\,x_3\right]^T=\left[C_A,T,T_j\right]^T$$

$$u=\left[u_1,u_2\right]^T=\left[F_{in},F_w\right]^T.$$

The description of variables for this CSTR model is given in [29], which is also listed in the Appendix.

The output responses of CSTR under the control of the DDC are shown in Fig. 6. The control signals of CSTR are shown in Fig. 7. The tracking error of CSTR is shown in Fig. 8. The tuning or design parameters for DDC are: $b_{0,11}=-0.5$, $b_{0,22}=-0.03$; $\omega_{c1}=\omega_{c2}=0.2$; $\omega_{o1}=\omega_{o2}=0.03$. The simulation results demonstrate that the highly nonlinear system is well controlled in the presence of high nonlinearity and cross-couplings. It has been shown that the closed-loop tracking error and its up to $(n-1)^{th}$ order derivatives monotonously decrease with the controller and observer bandwidths [30, 31].

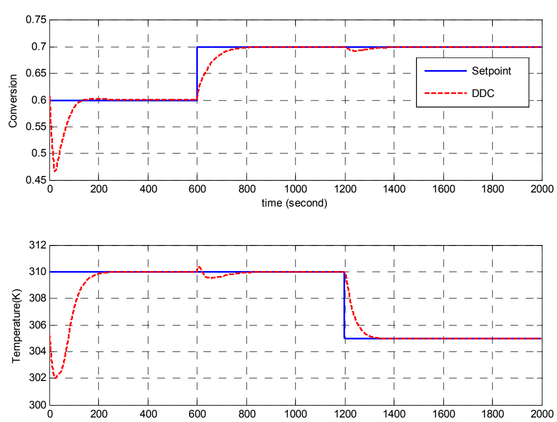

Fig. 6 The output response of CSTR under the control of the DDC.

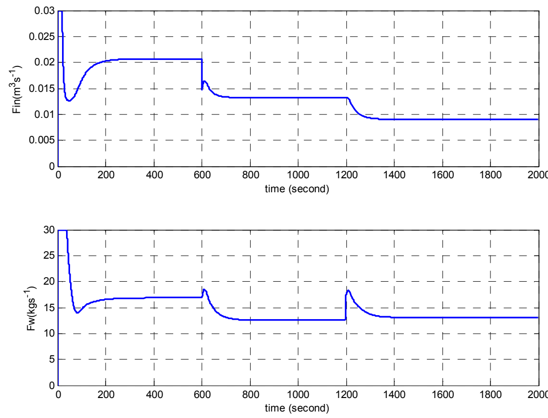

Fig. 7 The control signals of CSTR.

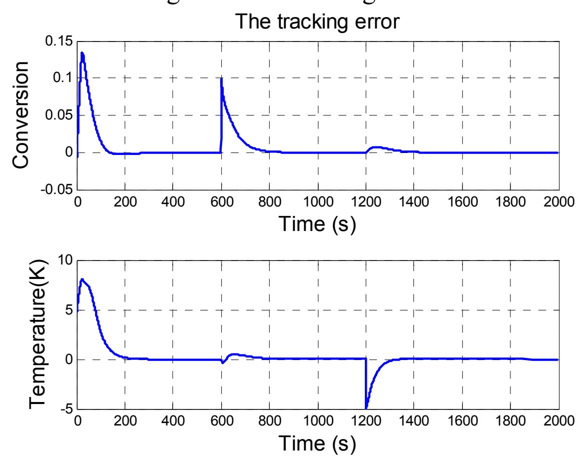

Fig. 8 The tracking error of CSTR.

IV. Concluding Remarks

In this paper, a novel decoupling control method is proposed for a class of square multivariable systems of various orders. It is based on a novel disturbance rejection concept and it does not require an accurate mathematical model. The proposed DDC method is easy to understand and to implement, which makes it quite practical. Simulation results applied to chemical processes are quite promising. Good performance is attained in two case studies involving both the linear and nonlinear multivariable plants with significant uncertainties.

Appendix: The Description of Variables for CSTR Model [29]

Variable	Value	Unit	Description
F_{in}		$kg\,s^{-1}$	The reactant feed flow rate
F_{out}		$kg\,s^{-1}$	The outlet flow rate
V	1	m^3	The volume of the tank reactor
c_A		kg/m^3	The concentration of species A inside the tank

$c_{A,in}$	866	kg/m^3	The concentration of species A at the feed
$c_{A,out}$		kg/m^3	The concentration of species A at the outlet
k_0	4.10^8	s^{-1}	Arrhenius rate constant
E	6.14	$Jmol^{-1}K^{-1}$	Activation energy
R	8.314	$Jmol^{-1}K^{-1}$	Gas law constant
T		K	Reactor temperature
ρ	866	$kg\ m^{-3}$	Density of the reactant
C_p	1.791	$J\ kg^{-1}\ K^{-1}$	Specific heat capacity of species A and B
T_{in}	293	K	Temperature of the inlet stream
U	30	W m^{-2} K^{-1}	Overall heat transfer coefficient
A	50	m^2	Heat transfer area
ΔH	-140	$J\ kg^{-1}$	Heat of reaction
T_j		K	Temperature of the cooling jacket
V_j	0.2	m^3	Volume of the cooling jacket
ρ_w	998	$kg\ m^{-3}$	Density of the water
C_{pw}	4.181	$J\ kg^{-1}\ K^{-1}$	Specific heat capacity of water
F_w		$kg\ s^{-1}$	Coolant water mass rate at the inlet and the outlet
T_w	290	K	Coolant water temperature at the jacket inlet

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