DISTURBANCE OBSERVER DESIGN FOR NONLINEAR SYSTEMS REPRESENTED BY INPUT-OUTPUT MODELS

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***Abstract*—A new approach to the design of nonlinear disturbance observers for a class of nonlinear systems described by input-output differential equations is presented in this paper. In contrast with established forms of nonlinear disturbance observers, the most important feature of this new type of disturbance observer is that only measurement of the output variable is required, rather than the state variables. An inverse simulation model is first constructed based on knowledge of the structure and parameters of a conventional model of the system. The disturbance can then be estimated by comparing the output of the inverse model and the input of the original nonlinear system. Mathematical analysis demonstrates the convergence of this new form of nonlinear disturbance observer. The approach has been applied to disturbance estimation for a linear system and a new form of linear disturbance observer has been developed. The differences between the proposed linear disturbance observer and the conventional form of frequency-domain disturbance observer are discussed through a numerical example. Finally, the nonlinear disturbance observer design method is illustrated through an application involving a simulation of a jacketed continuous stirred tank reactor system.**

***Index Terms*—Disturbance observer, nonlinear systems, inverse simulation model, continuous stirred-tank reactor system.**

I. INTRODUCTION

Dealing with discrepancies between properties of the real plant and its mathematical description has become one of the main problems of modern control theory, and many nonlinear control techniques have been developed to reduce the adverse effects of external disturbances, unmodeled dynamics and parameter uncertainties. Control design problems caused by such discrepancies may be approached in at least two ways. One involves robust control and the uses of feedback principles to suppress disturbances [1], [2]. However, such methods can present difficulties in terms of estimation of the disturbances or may tend to over-estimate their upper bounds [3], [4]. Also, the resulting gains of the state-feedback controllers tend to be large in order to provide enough control effort to reduce the effects of the disturbances [5]. It appears that such robust methods can lead to a worst-case-based design and the large values of gain factors can yield unsatisfactory dynamic and steady-state performance within the closed loop system [6], [7].

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* This work is supported by the National Science Foundation of China under Grants 61573170 and 31571571, the Jiangsu Natural Science Foundation for Distinguished Young Scholars under Grant BK20180045, the Priority Academic Program Development of Jiangsu Higher Education Institutions and the Six Talent Peaks Project in Jiangsu Province under Grant XNYQC-006.

The second approach is based on composite control principles and generally involves two steps [8]. The first step is to design a baseline feedback controller to satisfy the desired performance specifications for the nominal system (i.e., the nonlinear system without considering the disturbances). The second step is concerned with disturbance attenuation and, in the approach considered here, a disturbance observer (DOB) is used to estimate the disturbances. The estimated value is then taken as a feedforward term for compensation [9]. The baseline feedback controller plus the feedforward term constitute the composite controller. It is obvious that the feedforward term attenuates the adverse effects of the disturbances while the baseline feedback controller provides the required steady-state and dynamic performance and also suppresses any remaining disturbances. Due to the feedforward nature of the compensation and satisfaction of the prescribed specifications through use of the baseline feedback controller, the composite control schemes should provide excellent tracking performance and smooth control actions without the use of large feedback gains [10]–[12].

The fundamental idea of the DOB is to bring together all the internal uncertainties, external disturbances, parameter uncertainties and unmodeled dynamics as a single lumped disturbance term and then estimate this term by designing an observer. As described in [13], the DOB was developed by Ohnishi and his colleagues [14] in the early 1980s. The basic DOB block diagram was first proposed in terms of the frequency-domain. One important element of this block diagram is a low pass filter which allows the disturbance to be estimated in a low and medium frequency range but with high frequency measurement noise filtered out. Methods for design of this low-pass filter, which is of central importance in the frequency-domain DOB approach, can be found in [14], [15]. It should be noted that the conventional frequency-domain DOBs given in [14] require the linear systems being considered to have minimum-phase properties. The DOB design method has been extended recently to non-minimum-phase systems [16]. However, it should also be noted that the systems considered in [14], [16] are required to be linear or, alternatively, their nonlinear parts must be lumped together as a part of the disturbance variable.

For some inherently nonlinear systems the estimation performance with the linear DOB approach, outlined above, may not be satisfactory, since the design of the linear DOB is based on the linearization model of the nonlinear systems. Indeed, for many practical systems, the nonlinear dynamics are partially known. If these nonlinear dynamics can be taken into account, the performance in terms of estimation of the unknown lumped disturbances may be significantly improved. The first nonlinear DOB was developed by Chen [17], where a nonlinear DOB was constructed to estimate the disturbance torques caused by unknown friction in nonlinear robotic manipulators. Lyapunov analysis was used to verify the stability of the proposed nonlinear DOB system. The nonlinear DOB described in [17] was investigated further in [18] in the context of control performance improvements in a missile autopilot system. This work led on to a proposal for a general framework for nonlinear DOB design [19], where the disturbance is generated by an exogenous system. Another method, which may also be applied to the DOB design problem, involves reduced-order multiple observers. The main advantage of the reduced-order multiple observer approach relates to the decrease of the number of system sensors required. The concept of the reduced-order multiple observer was developed first in [20] where a reduced-order multiple observer was constructed for Takagi-Sugeno (T-S) systems with unknown inputs. Later, through the results in [20], a new reduced-order multiple observer was developed in [21] to achieve the finite-time reconstruction of the system's states associated with T-S multiple models. In addition, DOB techniques have been applied widely to many practical applications, such as the guidance law design for a hypersonic gliding vehicle [22], the attitude control of a spacecraft [23], and the direct yaw-moment control of an electric vehicle [24].

It may be seen that the approaches presented in [17]–[24] require system state variables to be available. This implies that if some state variables are not measurable these nonlinear DOB design methods cannot be applied. It should be pointed out that an output feedback design approach for SISO systems has been studied in [25], where a nonlinear DOB is constructed without measurements of the state variables. The proposed nonlinear DOB recovers not only the steady-state performance but also the transient performance of the nominal closed-loop system in the presence of plant uncertainties and input disturbances. The results in [25] have also been extended to the MIMO case in [26]. However, the systems considered in [25], [26] are characterized by some special structures and this restricts the application of this DOB design method.

Motivated by these important observations, this paper aims to develop a nonlinear DOB design method that uses only the output of the nonlinear system. The basic block diagram structure for a DOB system of this kind is shown in Fig. 1 where the plant output variable provides the input to a nonlinear inverse model block. In general, inverse dynamic models allow time histories of input variables to be found that correspond to a given set of output time history requirements. Thus, if one can construct the inverse dynamics of a nonlinear system, the disturbance can then be directly estimated using the type of approach suggested by the block diagram of Fig. 1. Inverse models of nonlinear systems have received much attention in recent years and several inverse simulation methods are available that allow inverse dynamic models to be implemented. Some of these were developed for specific application areas such as fixed-wing aircraft and helicopter handling qualities and agility investigations (see, e.g., [27], [28]) but have also been used with success for a number of other types of problems. The most widely used approaches have involved iterative methods and a useful review of these techniques, as developed for aeronautical applications, has been provided in [29]. Other approaches have been developed that are based on continuous system simulation principles and the most important of these has origins that can be traced back for more than sixty years to the use of feedback principles for operations such as division and inverse function generation in electronic analog computers. In more recent years the method was developed further and applied to more general problems of inverse modelling and simulation, as described in [30], [31] and [32], [33]. This approach has been adopted for the application considered in this paper, leading to development of a new form of nonlinear DOB which can be constructed for a class of nonlinear systems represented by input-output differential equations.

As described in [30] and [31]–[33], the inverse of the nonlinear system can be developed in a direct fashion using the ordinary differential equations which describe the plant model simply through the addition of high gain feedback. It has been shown that analysis based on linear minimum-phase models can be extended to the nonlinear case, not only for smooth nonlinearities but also for saturation and rate-limited dynamics [31]–[33]. In the context of DOB design those results imply that the disturbance may be estimated by subtracting the control input in the DOB block diagram (Fig. 1) from the reconstructed input obtained from the inverse simulation model. This offers the possibility of extending the inverse simulation approach based on feedback to provide a new form of nonlinear DOB for system described by nonlinear input-output ordinary differential equations. There are two main contributions in the paper. The first one is that a new DOB design method has been developed using only the information from the output and the control input, while the conventional nonlinear DOB requires the information relating to all the state variables. The second contribution is that the basic idea of developing the proposed nonlinear DOB is to construct the inverse of the original system, which is analogous to the conventional frequency-domain DOB.

II. Problem Formulation

In this paper, we consider the following nonlinear single-input-single-output (SISO) system described by an input-output differential equation of the following form:

$$y_1^{(n)} = f(Y_1) + g_0(Y_1)v + \cdots + g_m(Y_1)v^{(m)}, m \leq n \quad (1)$$

where $y_1 \in \mathbb{R}$ is the output variable;

$$Y_1 = (y_1, \dot{y}_1, \cdots, y_1^{(n-1)});$$

v is the input; $f(Y_1)$ and $g_i(Y_1), i = 0, 1, \cdots, m$, are smooth functions.

Remark 1: The input-output model (1) has been widely used to describe nonlinear systems in the literature, such as [34], [35], and also for the realization of the state-space descriptions of nonlinear systems, as described in [35]. Additionally, equation (1) also represents a large class of nonlinear systems which may be described as having flatness properties. Mathematical descriptions of this kind have been used in a wide range of applications, including the modelling of a DC electric motor [14] and virus dynamics [36]. As a matter of fact, in many practical systems, $g_i(Y_1), i = 1, \cdots, m$ directly equal to zero. When the actuator is considered, we may have $g_0 \neq 0, g_1 \neq 0$ and $g_i(Y_1) = 0, i = 2, \cdots, m$.

Generally speaking, the aim of control design is to ensure the stability or convergence of the output and, accordingly, it is reasonable to give the following assumption:

Assumption 1: There exists a proper control input u such that the output variable y_1 of system (1) and its higher-order derivatives $\dot{y}_1, \cdots, y_1^{(n-1)}$ are bounded.

In addition, system (1) also satisfies the following assumption

Assumption 2: The following dynamic system representation:

$$g_0(Y_1)v + g_1(Y_1)\dot{v} + \cdots + g_m(Y_1)v^{(m)} = 0 \tag{2}$$

is globally asymptotically stable.

Remark 2: It should be mentioned that Assumption 1 applies to almost all the nonlinear control systems that meet the conditions of smoothness stated already for (1). On the other hand, by a simple calculation, the zero dynamics of system (1) can be expressed as

$$g_0(0)v + \cdots + g_m(0)v^{(m)} = 0.$$

According to Assumption 2, we know that the dynamic system $g_0(0)v + \cdots + g_m(0)v^{(m)} = 0$ is globally asymptotically stable. This means that system (1) is minimum-phase and it appears that condition (2) can be considered as an extension of the minimum-phase property of system (1). In other words, condition (2) implies that the zero dynamics of system (1) represent a globally asymptotically stable situation. In the special case where system (1) is a linear system, the model can be rewritten as

$$\begin{aligned} &y_1^{(n)} + a_{n-1}y_1^{(n-1)} + \cdots + a_1\dot{y}_1 + a_0y_1 \\ &\quad = b_m v^{(m)} + b_{m-1}v^{(m-1)} + \cdots + b_0 v \end{aligned}$$

with some constants $a_i, i = 0, 1, \cdots, n-1$ and $b_j, j = 0, 1, \cdots, m$. Condition (2) can then be written as $b_m v^{(m)} + b_{m-1}v^{(m-1)} + \cdots + b_0 v = 0$, which leads directly to the minimum-phase property of the given linear system. It can be observed from the literature that there are many models of practical systems that satisfy Assumption 2, including the virus dynamics model [36], continuous stirred tank reactor model (CSTR) [37], the robotic manipulator system [38], the battery dynamics models [39], buck converter [40], etc.

The next step is to consider the disturbance estimation problem in the presence of a matched disturbance. That is, the disturbance is applied to the nonlinear system (1) in the same channel as the input. Therefore, the input v consists of the terms $u \in \mathbb{R}$ and $d(t) \in \mathbb{R}$ (i.e., $v = u + d(t)$), where u is the control input and $d(t)$ is the disturbance.

The goal of this paper is to design a DOB to estimate the disturbance $d(t)$ of the nonlinear system (1) by using only information from the control input u and the output variable y_1.

III. The New DOB Design for Nonlinear Systems

In this section, we will show how to construct a new form of nonlinear DOB based on the input-output model (1). The key technique involves the use of the inverse of the input-output model (1), and the methodology which has been applied is inspired directly by the inverse simulation work in [31]–[33].

To design the DOB for system (1) using the system structure of the input-output model, we first construct an auxiliary system as follows

$$y_2^{(n)} = f(Y_2) + g_0(Y_2)h + \cdots + g_m(Y_2)h^{(m)} \tag{3}$$

where the functions $f(Y_2)$ and $g_i(Y_2), i = 0, 1, \cdots, m$ with

$$Y_2 = (y_2, \dot{y}_2, \cdots, y_2^{(n-1)})$$

are defined to be the same as in that of (1), and y_2 and h are the output and input of system (3), respectively. Specifically, the input h can be defined as

$$h = K(y_1 - y_2) \tag{4}$$

where $K > 0$ is a sufficient large constant.

On this basis, the disturbance $d(t)$ can be estimated as

$$\hat{d}(t) = h - u. \tag{5}$$

The detailed block diagram of the nonlinear DOB for system (1) is given by Fig. 1. It can be seen clearly from (3)-(5) that the proposed new DOB only requires the system output y_1, and that higher-order derivatives of the output variable are not required in the DOB design.

Now we start to analyse the performance of the proposed nonlinear DOB (3)-(5). It will be shown that the output of the nonlinear DOB can gradually recover the unknown disturbance $d(t)$.

From Eq. (4), it follows that

$$\begin{cases} h & = K(y_1 - y_2) \\ \dot{h} & = K(\dot{y}_1 - \dot{y}_2) \\ \cdots & \\ h^{(n)} & = K\left(y_1^{(n)} - y_2^{(n)}\right), \end{cases} \tag{6}$$

which, in turn, implies that

$$\begin{cases} y_2 & = y_1 - \frac{h}{K} \\ \dot{y}_2 & = \dot{y}_1 - \frac{\dot{h}}{K} \\ & \vdots \\ y_2^{(n-1)} & = y_1^{(n-1)} - \frac{h^{(n-1)}}{K} \\ y_2^{(n)} & = y_1^{(n)} - \frac{h^{(n)}}{K}. \end{cases} \tag{7}$$

From the last equation of (7), we have $y_1^{(n)} = \frac{h^{(n)}}{K} + y_2^{(n)}$. This, together with (3), implies that

$$\begin{aligned} y_1^{(n)} = &\frac{h^{(n)}}{K} + f(Y_2) + g_0(Y_2)h + g_1(Y_2)\dot{h} \\ &+ \cdots + g_m(Y_2)h^{(m)}. \end{aligned} \tag{8}$$

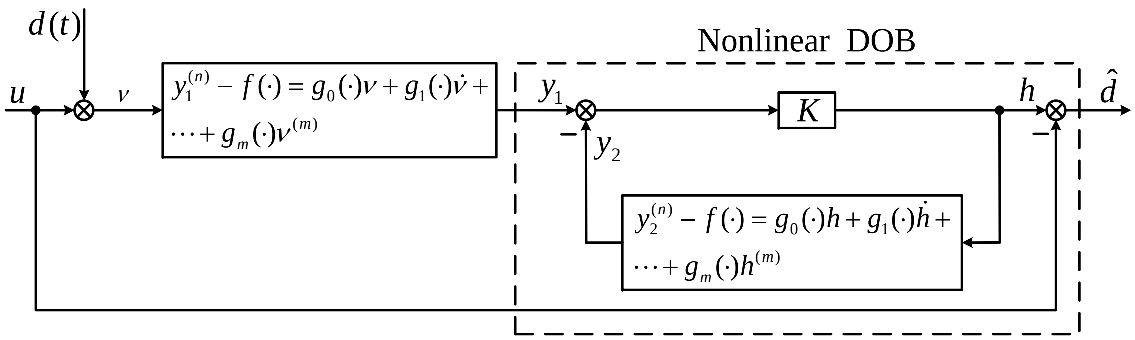

Fig. 1. Block diagram of the nonlinear DOB (3)-(5)

Applying Eq. (7) again to Eq. (8) yields

$$\begin{aligned} y_1^{(n)} = & \frac{h^{(n)}}{K} + f\left(y_1 - \frac{h}{K}, \dot{y}_1 - \frac{\dot{h}}{K}, \cdots, y_1^{(n-1)} - \frac{h^{(n-1)}}{K}\right) \\ & + g_0\left(y_1 - \frac{h}{K}, \dot{y}_1 - \frac{\dot{h}}{K}, \cdots, y_1^{(n-1)} - \frac{h^{(n-1)}}{K}\right) h \\ & + g_1\left(y_1 - \frac{h}{K}, \dot{y}_1 - \frac{\dot{h}}{K}, \cdots, y_1^{(n-1)} - \frac{h^{(n-1)}}{K}\right) \dot{h} \\ & + \cdots \\ & + g_m\left(y_1 - \frac{h}{K}, \dot{y}_1 - \frac{\dot{h}}{K}, \cdots, y_1^{(n-1)} - \frac{h^{(n-1)}}{K}\right) h^{(m)}. \end{aligned} \tag{9}$$

Adding and subtracting the same term $f(Y_1) + g_0(Y_1)h + g_1(Y_1)\dot{h} + \cdots + g_m(Y_1)h^{(m)}$ to the right-hand side of Eq. (9) gives

$$\begin{aligned} & y_1^{(n)} \\ & = f(Y_1) + g_0(Y_1)h + \frac{h^{(n)}}{K} \\ & \quad + g_1(Y_1)\dot{h} + \cdots + g_m(Y_1)h^{(m)} \\ & \quad + f\left(y_1 - \frac{h}{K}, \dot{y}_1 - \frac{\dot{h}}{K}, \cdots, y_1^{(n-1)} - \frac{h^{(n-1)}}{K}\right) \\ & \quad - f\left(y_1, \dot{y}_1, \cdots, y_1^{(n-1)}\right) \\ & \quad + \left(g_0\left(y_1 - \frac{h}{K}, \dot{y}_1 - \frac{\dot{h}}{K}, \cdots, y_1^{(n-1)} - \frac{h^{(n-1)}}{K}\right)\right. \\ & \quad \left. - g_0\left(y_1, \dot{y}_1, \cdots, y_1^{(n-1)}\right)\right) h \\ & \quad + \left(g_1\left(y_1 - \frac{h}{K}, \dot{y}_1 - \frac{\dot{h}}{K}, \cdots, y_1^{(n-1)} - \frac{h^{(n-1)}}{K}\right)\right. \\ & \quad \left. - g_1\left(y_1, \dot{y}_1, \cdots, y_1^{(n-1)}\right)\right) \dot{h} \\ & \quad + \cdots \\ & \quad + \left(g_m\left(y_1 - \frac{h}{K}, \dot{y}_1 - \frac{\dot{h}}{K}, \cdots, y_1^{(n-1)} - \frac{h^{(n-1)}}{K}\right)\right. \\ & \quad \left. - g_m\left(y_1, \dot{y}_1, \cdots, y_1^{(n-1)}\right)\right) h^{(m)}. \end{aligned} \tag{10}$$

Since the functions $f(y_1, \cdots, y_1^{(n-1)})$ and $g_j(y_1, \cdots, y_1^{(n-1)}), j = 0, \cdots, m$ are smooth functions, it can be concluded that the following inequalities hold, at least locally

$$\begin{aligned} & \left\| f\left(y_1 - \frac{h}{K}, \dot{y}_1 - \frac{\dot{h}}{K}, \cdots, y_1^{(n-1)} - \frac{h^{(n-1)}}{K}\right) - f\left(y_1, \cdots, y_1^{(n-1)}\right) \right\| \\ & \leq L_1 \left\| \left(\frac{h}{K}, \frac{\dot{h}}{K}, \cdots, \frac{h^{(n-1)}}{K}\right) \right\| = \frac{L_1}{K} \left\| \left(h, \dot{h}, \cdots, h^{(n-1)}\right) \right\| \end{aligned} \tag{11}$$

and

$$\begin{aligned} & \left\| g_i\left(y_1 - \frac{h}{K}, \dot{y}_1 - \frac{\dot{h}}{K}, \cdots, y_1^{(n-1)} - \frac{h^{(n-1)}}{K}\right) - g_i\left(y_1, \cdots, y_1^{(n-1)}\right) \right\| \\ & \leq L_2 \left\| \left(\frac{h}{K}, \frac{\dot{h}}{K}, \cdots, \frac{h^{(n-1)}}{K}\right) \right\| \\ & = \frac{L_2}{K} \left\| \left(h, \dot{h}, \cdots, h^{(n-1)}\right) \right\| \end{aligned} \tag{12}$$

with L_1 and L_2 being Lipschitz constants.

Let $H_1 = \left\| \left(h, \dot{h}, \cdots, h^{(n-1)}\right) \right\|$. Substituting (11) and (12) into (10) implies that

$$\begin{aligned} & \left| y_1^{(n)} - f(Y_1) - g_0(Y_1)h - g_1(Y_1)\dot{h} - \cdots - g_m(Y_1)h^{(m)} \right| \\ & \leq \frac{|h^{(n)}|}{K} + \frac{L_1}{K}H_1 + \frac{L_2}{K}H_1\left(|h| + |\dot{h}| + \cdots + |h^{(m)}|\right). \end{aligned} \tag{13}$$

It follows from Eq. (13) that

$$\frac{\left| y_1^{(n)} - f(Y_1) - g_0(Y_1)h - \cdots - g_m(Y_1)h^{(m)} \right|}{|h^{(n)}| + L_1H_1 + L_2\left(H_1|h| + \cdots + H_1|h^{(m)}|\right)} \leq \frac{1}{K}. \tag{14}$$

When $K \to \infty$, one has

$$y_1^{(n)} = f(Y_1) + g_0(Y_1)h + g_1(Y_1)\dot{h} + \cdots + g_m(Y_1)h^{(m)}. \tag{15}$$

Combining (15) and (1) gives

$$g_0(Y_1)(h - v) + g_1(Y_1)(\dot{h} - \dot{v}) + \cdots + g_m(Y_1)\left(h^{(m)} - v^{(m)}\right) = 0. \tag{16}$$

Letting the error e_1 be $e_1 = h - v$, it follows from (16) that

$$g_0(Y_1)e_1 + g_1(Y_1)\dot{e}_1 + \cdots + g_m(Y_1)e_1^{(m)} = 0. \tag{17}$$

From Assumption 2, we know that system (17) is globally asymptotically stable. Therefore, the error between h and v approaches zero asymptotically, which implies that h converges to v. Hence, the estimate $\hat{d}(t)$ converges asymptotically to the disturbance $d(t)$.

Remark 3: It can be seen from (17) that the estimation error will asymptotically converge to zero, provided the gain K tends to infinity. T hus, t he p roposed D OB a ppears t o b e a form of high-gain observer, but this is not the case. More specifically, i t c an b e o bserved f rom [41], [42] t hat high-gain observers are used to estimate the states of nonlinear systems, while the purpose of the proposed DOB is estimation of the disturbances. Also, the basic idea of the proposed DOB is to reconstruct an inverse model of the original system, which is different from the framework of Khalil's high-gain observer. On the other hand, the point may be that both kinds of controllers use high gains to suppress the effect of the disturbances.

Remark 4: It can be deduced from Assumption 2 that system (1) can be rewritten as a Brunovsky form in the state space. We should note that the system in Brunovsky form represents a variety of practical systems, whose disturbances may be estimated by using an extended state observer (ESO) [43] or Arie Levant's differentiator [44], [45]. One point we should mention is that in order to estimate the disturbances of system (1) the proposed DOB only requires the information relating to the control input and output variables. However, apart from the information relating to the control input and output, the ESO [43] and Levant's differentiator in [44], [45] also need information concerning the derivatives of the output or state variables.

Remark 5: We should note that the conventional DOB design has been widely applied to many kinds of nonlinear systems, such as those discussed in [46], [47]. However, it can be seen clearly from [46], [47] that accurate information relating to the control input and state variables must be available. The main difference between the proposed nonlinear DOB and the conventional type of DOB lies in the fact that the proposed form of observer requires only information relating to the control input and output variable. This implies that the conventional DOB design methods can not be applied to the systems considered in this paper.

IV. Performance analysis

In this section, we will show how the parameter K affects the performance of the nonlinear DOB (3)-(5).

By Assumption 1 and the information about the structure of the DOB in (3)-(5), it is clear that $y_1, \dot{y}_1, \cdots y_1^{(n)}$ and $h, \dot{h}, \cdots h^{(n)}$ are at least locally bounded. Therefore, for a large enough K, we can obtain from (14) that there exists a constant λ such that

$$\left|y_1^{(n)} - f\left(Y_1\right) - g_0\left(Y_1\right)h - \cdots - g_m\left(Y_1\right)h^{(m)}\right| \leq \frac{|h^{(n)}| + L_1 H_1 + L_2(H_1|h| + \cdots + H_1|h^{(m)})}{K} \leq \lambda.$$

This, together with (1), implies that

$$|g_0\left(Y_1\right)e_1 + g_1\left(Y_1\right)\dot{e}_1 + \cdots + g_m\left(Y_1\right)e_1^{(m)}| \leq \lambda, \quad (18)$$

which means that the estimation error will converge to a region around the origin in a finite-time interval.

On the other hand, if there is measurement noise ΔY_1 and lumped disturbances, including system uncertainties and external disturbances in the input-output model (1), then by a simple calculation, inequality (18) can be rewritten as

$$\begin{aligned}|g_0\left(Y_1 + \Delta Y_1\right)e_1 + g_1\left(Y_1 + \Delta Y_1\right)\dot{e}_1 + \cdots \\ + g_m\left(Y_1 + \Delta Y_1\right)e_1^{(m)}| \leq \lambda + \Delta\end{aligned} \quad (19)$$

with Δ being the upper bound of the lumped disturbance. It is clear that the estimation error will still converge to a region around the origin determined by the parameter λ and the upper bound of the lumped disturbance Δ.

To build up further understanding of the proposed DOB design techniques, we want to compare the proposed new nonlinear DOB with the existing ones. However, it can be seen that all the existing nonlinear DOBs require the information relating to the state variables or the output and its higher-order derivatives. There is clearly no basis for making comparisons and therefore the special case for linear systems is discussed and then compared with the existing DOB techniques based on the input and output model.

Consider the following linear system

$$\begin{aligned}y_1^{(n)} + a_{n-1}y_1^{(n-1)} + \cdots + a_1\dot{y}_1 + a_0 y_1 \\ = b_m v^{(m)} + b_{m-1}v^{(m-1)} + \cdots + b_0 v\end{aligned} \quad (20)$$

where $v = u + d(t)$, the positive integers $n \geq m$, $a_i, i = 0, 1, \cdots, n-1$ and $b_j, j = 0, 1, \cdots, m$ are known system parameters. Based on Assumptions 1-2, system (20) satisfies the following assumption

Assumption 3: Linear system (20) is stable and minimum-phase.

The new linear DOB for system (20) can be constructed as

$$\hat{d} = h - u \quad (21)$$

where h is defined as

$$h = K(y_1 - y_2), \quad (22)$$

with $K > 0$ being a sufficiently large constant and y_2 being generated by the following auxiliary system

$$\begin{aligned}y_2^{(n)} + a_{n-1}y_2^{(n-1)} + \cdots + a_1\dot{y}_2 + a_0 y_2 \\ = b_m h^{(m)} + b_{m-1}h^{(m-1)} + \cdots + b_0 h.\end{aligned} \quad (23)$$

The structure of DOB for system (20) is shown in Fig. 2.

In the following, we will show the convergence of the linear DOB described by Eqs. (21)-(23). From (22), we can also obtain a relation of the same form as (7) which has the specific form

$$y_2 = y_1 - \frac{h}{K},\ y_2^{(i)} = y_1^{(i)} - \frac{h^{(i)}}{K}, i = 1, \cdots, n. \quad (24)$$

Using the auxiliary system equation (23), we have

$$\begin{aligned}h^{(n)} &= K(y_1^{(n)} - y_2^{(n)}) \\ &= Ky_1^{(n)} - K(b_m h^{(m)} + b_{m-1}h^{(m-1)} + \cdots + b_0 h \\ &\quad - a_{n-1}y_2^{(n-1)} - \cdots - a_1\dot{y}_2 - a_0 y_2).\end{aligned} \quad (25)$$

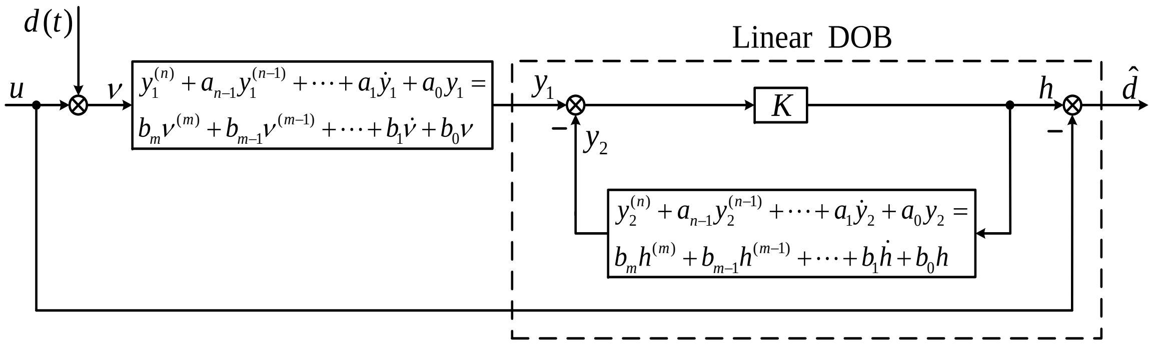

Fig. 2. Block diagram of the linear DOB (21)-(23).

Substituting (24) into (25) yields

$$\begin{aligned} &h^{(n)} \\ &= Ky_1^{(n)} - K\left(b_m h^{(m)} + b_{m-1}h^{(m-1)} + \cdots + b_0 h\right) \\ &\quad + K\left(a_{n-1}\left(y_1^{(n-1)} - \frac{h^{(n-1)}}{K}\right) + \cdots \right. \\ &\quad \left. + a_1\left(\dot{y}_1 - \frac{\dot{h}}{K}\right) + a_0\left(y_1 - \frac{h}{K}\right)\right) \end{aligned} \tag{26}$$

and it follows that

$$\begin{aligned} h^{(n)} = Ky_1^{(n)} &- K\left(b_m h^{(m)} + b_{m-1}h^{(m-1)} + \cdots + b_0 h\right) + \\ &K\left(a_{n-1}y_1^{(n-1)} + \cdots + a_1\dot{y}_1 + a_0 y_1\right. \\ &\left. - \frac{1}{K}\left(a_{n-1}h^{(n-1)} + \cdots + a_1\dot{h} + a_0 h\right)\right). \end{aligned} \tag{27}$$

System (27) can be rewritten as

$$\begin{aligned} &h^{(n)} + a_{n-1}h^{(n-1)} + \cdots + a_1\dot{h} + a_0 h \\ &= K\left(y_1^{(n)} + a_{n-1}y_1^{(n-1)} + \cdots + a_1\dot{y}_1 + a_0 y_1\right) \\ &\quad - K\left(b_m h^{(m)} + b_{m-1}h^{(m-1)} + \cdots + b_0 h\right). \end{aligned} \tag{28}$$

Both sides of Eq. (28) divided by $K(h^{(n)} + a_{n-1}h^{(n-1)} + \cdots + a_1\dot{h} + a_0 h)$ yields

$$\begin{aligned} &\frac{y_1^{(n)} + a_{n-1}y_1^{(n-1)} + \cdots + a_1\dot{y}_1 + a_0 y_1}{h^{(n)} + a_{n-1}h^{(n-1)} + \cdots + a_1\dot{h} + a_0 h} \\ &- \frac{b_m h^{(m)} + b_{m-1}h^{(m-1)} + \cdots + b_0 h}{h^{(n)} + a_{n-1}h^{(n-1)} + \cdots + a_1\dot{h} + a_0 h} = \frac{1}{K}. \end{aligned} \tag{29}$$

When $K \to \infty$, one has

$$\begin{aligned} &y_1^{(n)} + a_{n-1}y_1^{(n-1)} + \cdots + a_1\dot{y}_1 + a_0 y_1 \\ &= b_m h^{(m)} + b_{m-1}h^{(m-1)} + \cdots + b_1\dot{h} + b_0 h. \end{aligned} \tag{30}$$

From (20) and (30), we also get

$$\begin{aligned} &b_m v^{(m)} + b_{m-1}v^{(m-1)} + \cdots + b_1\dot{v} + b_0 v \\ &= b_m h^{(m)} + b_{m-1}h^{(m-1)} + \cdots + b_1\dot{h} + b_0 h. \end{aligned} \tag{31}$$

And if we let $e_2 = v - h$, it follows from (31) that

$$b_m e_2^{(m)} + b_{m-1}e_2^{(m-1)} + \cdots + b_1\dot{e}_2 + b_0 e_2 = 0. \tag{32}$$

From Assumption 3, we know that system (20) is minimum-phase. This implies that the polynomial $b_m s^m + b_{m-1}s^{m-1} + \cdots + b_1 s + b_0 = 0$ is Hurwitz stable. Thus, we have $e_2 \to 0$ and $h \to v = u + d$. Hence, we may conclude that the disturbance $d(t)$ can be estimated as $h - u$.

It should be mentioned that the disturbance in system (20) can also be estimated well by using the conventional frequency-domain DOB proposed in [14], [43]. In the case of the frequency-domain DOB methodology, the key point is how to choose the parameters for the low-pass filter $Q(s)$ shown in Fig. 4. This is especially important for higher-order cases and it is important to note that in the proposed method, as shown in (21)-(23), there is only one parameter, K, which must be adjusted. In comparison with the conventional frequency-domain DOB, the choice in terms of the specific value for the tuning parameter for this new form of DOB given in (21)-(23) will thus be significantly more straightforward.

Remark 6: From a theoretical viewpoint, it is clear that the use of larger values of parameter K implies improved estimation performance. On the other hand, increasing the value of K may increase the noise level at the output. This implies that the gain K has to be chosen to have a moderate value. A basic rule is to adjust the tuning parameter K from an initial small value to larger values until the performance requirements are satisfied.

In the following, we will compare the proposed linear DOB (21)-(23) with the conventional frequency-domain DOB using a numerical example, which also shows how the performance is affected by the parameter K and the noise level at the output.

Example 1: Consider a linear system described by the following transform function

$$G(s) = \frac{s+1}{s^3 + 9s^2 + 26s + 24}. \tag{33}$$

Assume that the disturbance $d(t)$ is defined as

$$d(t) = d_0(t) + \sin(y_1) + 0.5u$$

where

$$d_0(t) = \begin{cases} 2\sin\left(\frac{t}{4}\right) & 0 \le t < 16\pi \\ 0.7\sin(t) & 16\pi \le t < 100. \end{cases} \tag{34}$$

Let the input signal be $u = \sin(t)$ and the sampling time is taken as 0.0001s. Fig. 3 shows the performance comparisons of the proposed linear DOB (21)-(23) for four different values

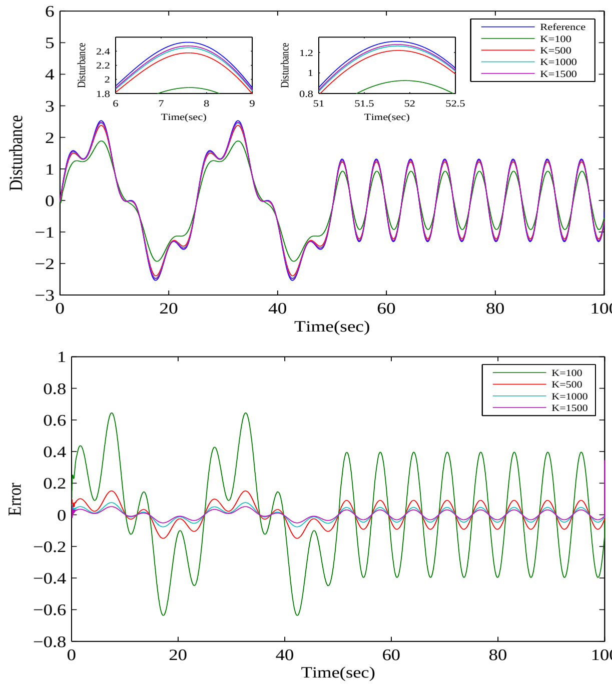

Fig. 3. Time response of $\hat{d}(t)$ and estimation error for the DOB (21)-(23) for several different values of the adjustable parameter K

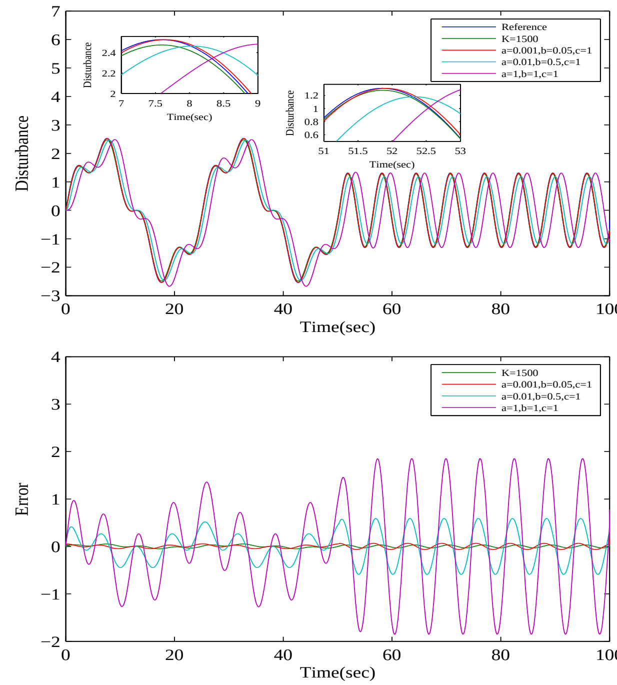

Fig. 5. Time response of $\hat{d}(t)$ and estimation error for the conventional frequency-domain DOB and the DOB (21)-(23) with $K = 1500$

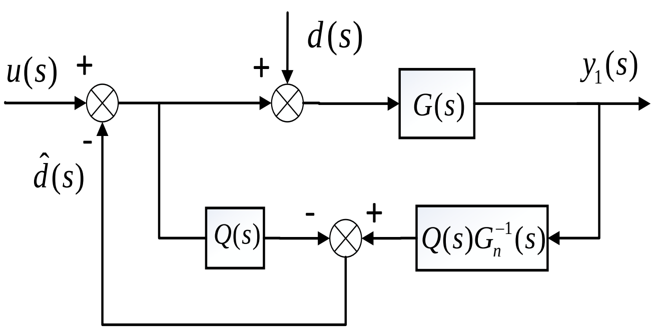

Fig. 4. Diagram of conventional frequency-domain DOB

of the parameter K. From Fig. 3, it can be seen clearly that larger values of K give increased estimation accuracy.

Comparisons between DOB (21)-(23) and the conventional frequency-domain DOB are also necessary. According to the frequency-domain DOB theory given in [43], we design a conventional linear DOB for system (33) having the form shown in Fig. 4, where $G_n(s)$ and $Q(s)$ are designed as

$$G_n(s) = \frac{s+1}{s^3 + 9s^2 + 26s + 24}, \quad Q(s) = \frac{1}{as^2 + bs + c}.$$

with some proper constants a, b and c.

Choosing the parameters (a, b, c) in $Q(s)$ as $(0.001, 0.05, 1)$, $(0.01, 0.5, 1)$ and $(1, 1, 1)$, respectively provides three set of results for the frequency-domain DOB, as shown in Fig. 5. Those results include a comparison with the performance obtained using the proposed DOB structure with $K = 1500$. It can also be observed from Fig. 5 that when the parameters of the filter $Q(s)$ are properly chosen, the estimation performance of the two types of DOB is similar. It should be pointed out that the performance of the conventional frequency-domain DOB depends on the choice of the parameters for $Q(s)$ which can present difficulties. By contrast, the choice of K in DOB (21)-(23) is much easier. The maximum errors for these DOBs are also given in Table I. It can be seen clearly from Table I that larger values of K produce smaller values of the estimation error.

TABLE I
MAXIMUM ERROR FOR DIFFERENT CASES

Case	Maximum Error
$K = 100$	0.6448
$K = 500$	0.1509
$K = 1000$	0.0771
$K = 1500$	0.0518
$a = 0.001$, $b = 0.05$, $c = 1$	0.0654
$a = 0.01$, $b = 0.5$, $c = 1$	0.5900
$a = 1$, $b = 1$, $c = 1$	1.8484

One additional point that must be considered concerns the estimation accuracy in the presence of output noise and parameter perturbations. For this it is assumed that a small amount of random noise (2%) and parameter perturbation (8%) are added to system (33). The corresponding simulation results are given in Fig. 6, which indicates that the large values of K may lead to increased noise levels. This suggests that in selecting the parameter K account must be taken of output noise levels and K cannot be made arbitrarily large.

V. NONLINEAR DOB DESIGN EXAMPLE

In this section, the nonlinear DOB (3)-(5) will be applied to a continuous stirred tank reactor (CSTR) system model to evaluate its performance through simulation.

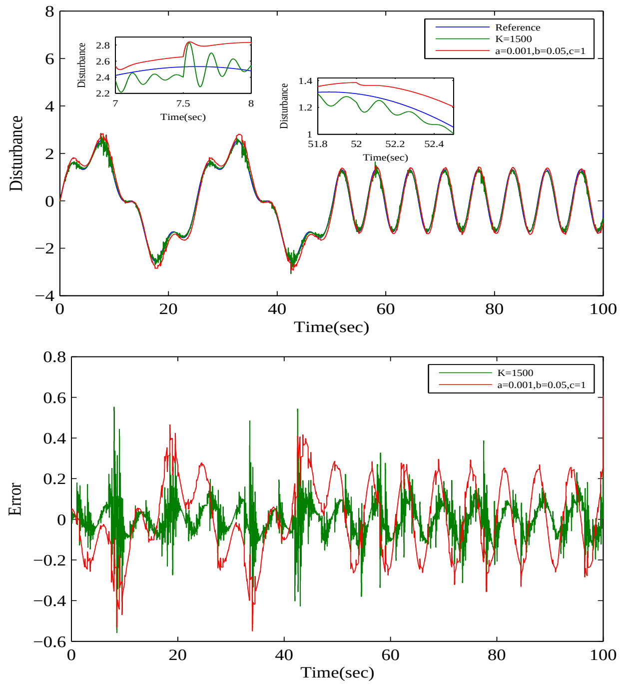

Fig. 6. Time response of $\hat{d}(t)$ and estimation error for the DOB (21)-(23) with additional random noise (2%) and parameter perturbation (8%)

Consider a jacketed CSTR system involving reactor mass balance, reactor energy balance and the cooled jacket energy balance [37]. Specifically, in this model, the reactor mass balance can be described by:

$$\dot{x}_1 = q(u_1 - x_1) - 0.072F(x_2)x_1 + d(t) \tag{35}$$

while the reactor energy balance is

$$\dot{x}_2 = q(u_2 - x_2) + 0.576F(x_2)x_1 - 0.3(x_2 - x_3) \tag{36}$$

and the cooled jacket energy balance is

$$\dot{x}_3 = \delta_1 q_c(u_3 - x_3) + 3(x_2 - x_3) \tag{37}$$

where $F(x_2) = e^{\frac{x_2}{1+x_2/20}}$ is the kinetic constant, x_1 is the concentration of the chemical reactive, u_1 is the reactive input concentration, $d(t)$ is the disturbance including external temperature variations, chemical feed quality, sulphur particle levels, parameter perturbations and the effects of cross-couplings, etc. The variable x_2 is the reactor temperature, u_2 is the input reactor temperature, x_3 is the cooled jacket temperature, u_3 is the input cooled jacket temperature, q is the inverse of the residence time, q_c is the inverse of the residence time of the cooled jacket and δ_1 is a parameter.

In this model, x_2 and x_3 are normally regarded as measurable, while the variable x_1 is considered as unmeasurable as any measurement may be very expensive or even impossible. Therefore, the outputs of CSTR model are usually chosen as:

$$y_1 = x_2, \quad z_1 = x_3.$$

The objective here is to design a DOB based on the output variables y_1 and z_1 to estimate the disturbance $d(t)$.

First of all, from (36), one has

$$x_1 = \frac{\dot{y}_1 + 0.3(y_1 - z_1) - q(u_2 - y_1)}{0.576F(y_1)}, \quad F(y_1) = e^{\frac{y_1}{1+y_1/20}}$$

which implies that

$$\dot{x}_1 = \frac{F(y_1)[\ddot{y}_1 + 0.3(\dot{y}_1 - \dot{z}_1) + q\dot{y}_1]}{0.576F^2(y_1)} - \frac{\dot{F}(y_1)[\dot{y}_1 + 0.3(y_1 - z_1) - q(u_2 - y_1)]}{0.576F^2(y_1)}.$$

It follows from (35) that $qu_1 + d(t) = \dot{x}_1 + qx_1 + 0.072F(y_1)x_1$. This implies that

$$\begin{aligned} qu_1 + d(t) =& \frac{q + 0.072F(y_1)}{0.576F(y_1)}[\dot{y}_1 + 0.3(y_1 - z_1) - q(u_2 - y_1)] \\ &+ \frac{F(y_1)[\ddot{y}_1 + 0.3(\dot{y}_1 - \dot{z}_1) + q\dot{y}_1]}{0.576F^2(y_1)} \\ &- \frac{\dot{F}(y_1)[\dot{y}_1 + 0.3(y_1 - z_1) - q(u_2 - y_1)]}{0.576F^2(y_1)}. \end{aligned}$$

And, by a simple calculation, it may be seen that

$$\begin{aligned} &\ddot{y}_1 + (q+0.3)\dot{y}_1 - 0.3\dot{z}_1 \\ &+ [\dot{y}_1 + 0.3(y_1 - z_1) - q(u_2 - y_1)]\left[q + 0.072F(y_1) - \frac{\dot{F}(y_1)}{F(y_1)}\right] \\ &= 0.576qF(y_1)\left[u_1 + \frac{d(t)}{q}\right]. \end{aligned} \tag{38}$$

Under normal working conditions, the concentration of the chemical reactive x_1, the reactor temperature x_2 and the cooled jacket temperature are always bounded. This implies that the output y_1 and its derivative will be bounded, which also means that Assumption 1 holds. In addition, by (38), we can let $v = u_1 + \frac{d_1(t)}{q}$ and $g_0(Y_1) = 0.576qF(y_1)$. Since $g_0(Y_1) > 0$, it follows directly that Assumption 2 holds. Then, from DOB (3)-(5), the disturbance $d(t)$ can be estimated as

$$\hat{d} = q(h - u_1) \tag{39}$$

with $h = K(y_1 - y_2)$ and y_2 being generated by

$$\begin{aligned} &\ddot{y}_2 + (q+0.3)\dot{y}_2 - 0.3\dot{z}_1 + [\dot{y}_2 + 0.3(y_2 - z_1) - q(u_2 - y_2)] \\ &\times \left[q + 0.072F(y_2) - \frac{\dot{F}(y_2)}{F(y_2)}\right] = 0.576qF(y_2)h. \end{aligned}$$

The block diagram of the control system is given as in Fig. 7.

Let the inputs and parameters of the CSTR system be $u_1 = 1, u_2 = 0, u_3 = -1$ and $K = 69, q = 1, q_c = 0.28, \delta_1 = 10$, respectively. The initial states are chosen as $x_1(0) = 0.58, x_2(0) = 2.67, x_3(0) = 0.12$. Here we assume that the the disturbance $d(t)$ is given as

$$d(t) = \begin{cases} 0 & 0 \le t < 2 \\ 1 & 2 \le t < 20 \\ -\frac{t}{10} + 3 & 20 \le t < 30 \\ 2\sin\left(\frac{t-30}{4}\right) & 30 \le t < 30 + 8\pi \\ 0.7\sin(t-30) & 30 + 8\pi \le t < 30 + 17\pi \\ 0 & t \ge 30 + 17\pi \end{cases} \tag{40}$$

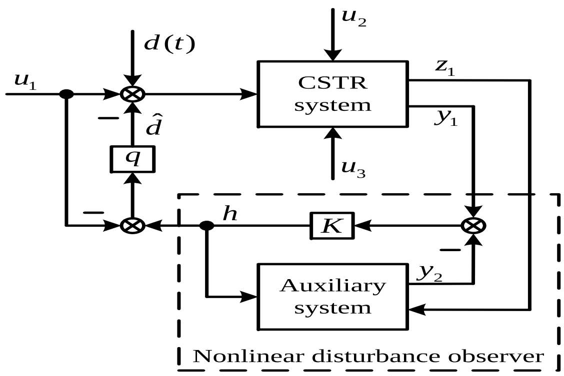

Fig. 7. Block diagram of CSTR system with nonlinear DOB

The simulation result is shown in Fig. 8 and it can be observed clearly that the disturbance is estimated well.

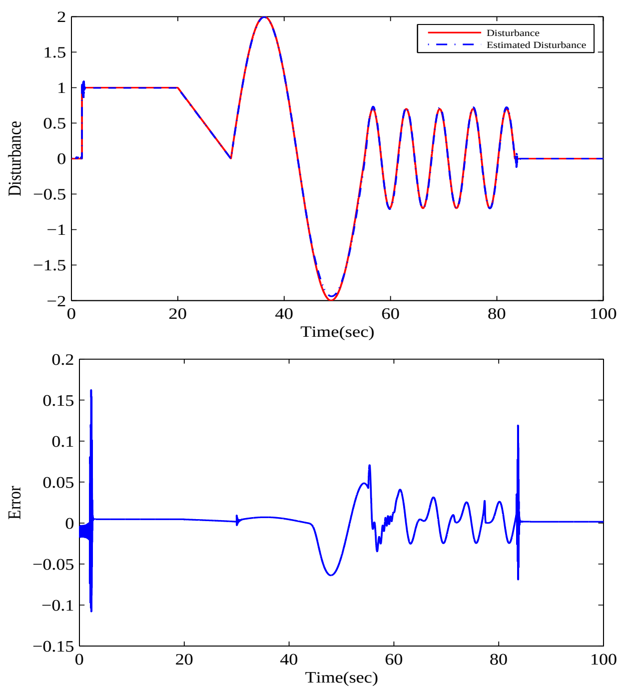

Fig. 8. The disturbance estimation and error for CSTR system (35)-(36)-(37)

VI. Conclusions

This paper proposes a new DOB design method for a class of nonlinear systems based on input-output representations. It overcomes the restriction that applies currently to all disturbance observer design methods for nonlinear systems that all the state variables must be measurable. It is shown that by using only the input and output variables of a nonlinear system, the estimate yielded by the proposed DOB can asymptotically converge to the disturbance. This work provides the first step in the development of a general disturbance observer design method for nonlinear systems based on an input-output representation. It is required that the input-output model satisfies a minimum-phase-like property. The special case of the proposed DOB design method for linear systems was also presented and compared with the existing DOB design method using the input-output description. Our future work will focus on applying this method to practical cases, with experimental tests, and extending the proposed results to MIMO systems and problems involving mismatched disturbances. And we will also develop new nonlinear disturbance observer techniques for systems being unstable or with unstable zero dynamics.

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