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Unknown Input Observer-Based Decentralized PID-BFO Algorithm for Interconnected Systems Against Fault Actuator

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Abstract- *This article presents a decentralized controller/observer for nonlinear large-scale interconnected systems with actuator fault. The proposal integrates a robust proportional-integral-derivative (PID) controller with the unknown input observer (UIO) to achieve closed-loop robustness against the interactions and the actuator faults. In this scheme, the PID controller is tuned using the Bacterial foraging optimization algorithm (BFO) algorithm. On the other hand, the unknown input observer can diagnose the actuator faults from the controller input. A numerical example consisting of two subsystems is adopted to clarify the effectiveness of the suggested method with a guarantee that the state estimation error is asymptotically converged to zero. The actuator faults have been added to the second subsystem, keeping the first subsystem free of fault. The simulation results demonstrated the influence of the interactions between subsystems, verifying that the unknown input observer can detect the actuator faults despite the presence of these interactions between the subsystems.*

Index Terms*—Fault Diagnosis (FD), Unknown Input Observer (UIO), Proportional- Integral-Derivative (PID), Bacterial Foraging Optimization (BFO).*

I. INTRODUCTION

Large-Scale Systems (LSS) are composed of a set of interconnected subsystems [1-2]. Various control schemes such as decentralized, centralized, and distributed controls have been adopted for such systems [3]. Generally, exchanging information between subsystems is a significant challenge in controller design for large-scale systems [4]. Such a challenge attracts researchers to decentralized control to avoid information exchange between subsystems, making the controller more straightforward to design.

The local PI algorithm for nonlinear interconnected systems with unknown interconnections used in the frame of decentralized control is proposed in [5]. The use of adaptive decentralization Fault-Tolerant Control (FTC) was examined for uncertain nonlinear interconnected systems in [6]. Y. Zhu and E. Fridman suggested compensation for significant delays in large-scale systems by a decentralized predictor-based resultant feedback [7].

It is worth mentioning that failure in one or more subsystems deteriorates the response of the whole interconnected system. The control system depends on its performance on the actuators' action and the sensor's measurements. Thus, when actuators or sensors are prone to faults, the entire system's stability might be violated [8]. Such operating conditions make diagnosing faults and FTC necessary. Although fault diagnosis is difficult, it is pivotal for FTC because it is commonly dependent on the information provided by fault diagnosis [9]. Fault detection, fault isolation, and fault estimation are the three primary functions of a fault diagnosis system [10]. The first step in fault diagnosis is fault detection which is used to

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decide the system's functioning circumstances, specifically whether or not it is operating normally. The next step is fault isolation to determine where the faults occur [10]. Generally, most diagnosis systems include Fault Detection and Isolation (FDI). However, FDI cannot provide extra information about the faults like their nature, position, and magnitude. The step of fault estimation can provide this information, which means that when faults are correctly estimated, they are also correctly detected and isolated [10].

Researchers have considered fault diagnosis methods against the simultaneous sensor and actuator faults for various applications. In [11-12], the authors have proposed a review of fault diagnosis and fault-tolerant techniques in different applications. Compensation of sensor fault using adaptive resultant feedback control is suggested in [13]. The data-driven method was used against various sensor faults in PID systems with variable gain [14].

Observer plays a significant role in fault diagnosis. It uses input and output information of the model to observe the consistency between the output of the predicted model and basic information [15]. The paper integrates the Unknown Input Observer (UIO) and PID-based BFO algorithm for large-scale nonlinear systems, and the main contributions are:

1- Design a robust PID-BFO controller to guarantee robust stability against actuator and subsystems interaction. Specifically, the ability of PID-BFO to maintain zero reference signal tracking error has been employed to guarantee closed-loop robustness against actuator fault and interactions.
2- Demonstrate the effectiveness of UIO to make the estimation error converge to zero, despite the presence of interactions and fault. In this concern, robust actuator fault detection is achieved by decoupling interactions' effects locally.
3- Design a decentralized controller/observer based on the PID-BFO algorithm with UIO for LSS.

The article can be arranged as follows: Section II describes the interconnected systems. Section III explains the PID controller tuning by the BFO algorithm. Section IV describes the design of UIO. A numerical example is suggested in section V. Final section displays the conclusion with the future works.

II. DEVELOPMENT OF INTERCONNECTED SYSTEMS

The nonlinear interconnected systems can be described in (1), it consists of a set of n subsystems:

$$\dot{x}_i(t) = A_i x_i(t) + B_i u_i(t) + \sum_{j\neq i}^{n} A_{ij} x_j(t) + f_i(x_i, u_i, f_{ai}, d) \quad (1)$$
$$for\ i = 1, 2, \dots, n$$

$$y_i = C_i x_i(t) \quad (2)$$

where $y_i(t) \in R^{ri}$ is the measured output, $x_i(t) \in R^{ni}$, is the state vector, $u_i(t) \in R^{mi}$ is the vector of control input, $f_i(x_i, u_i, f_{ai}, d) \in R^{ni}$ is the parameters of *i_th* subsystem and which is consist of nonlinearities, uncertainties, and external disturbance of *i_th* subsystem, and $f_{ai}(t) \in R^{mi}$ represent the actuator fault [16].

A_i, B_i, C_i, A_{ij} are the state, input, output, and interconnection matrices, respectively [16]; suppose that the original systems (A_i, C_i), $i = 1,2,\dots,n,$ are completely observable and (A_i, B_i), $i = 1,2,\dots,n,$ are completely controllable. Both (A_i, B_i) and (A_i, C_i) are assumed to be detectable and stabilizable. Considering that the output for each subsystem is available, the interactions between subsystems are unknown.

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III. PID CONTROLLER TUNING BY BFO ALGORITHM

PID is one of the classical controllers used by many researchers for its simplicity [17]. It is versatile in use, and its parameters are adjusted to particular needs [18]. It directs the output response as required by the user's specifications. Its parameters are adjusted with high accuracy to achieve optimum performance [19] because it directly affects the performance of the controller's system [20]. The general form of PID controller is:

$$u(t) = k_p e(t) + k_i \int_0^t e(\tau)d\tau + k_d \frac{d}{dt} e(t) \quad (3)$$

Where: k_p, k_i, k_d, $e(t)$ are proportional, integral, derivative gains and the error of time, respectively [21].

Several algorithms are used for tuning the PID controller, including the bacterial foraging optimization (BFO) algorithm, which depends on the mechanism of E.coli during the search process. The BFO algorithm is composed of four stages [22]:

1. Chemotaxis: This process is the basis of the algorithm, as it mimics the swimming behaviour and regression of Escherichia Coli. (E. Coli) behaviour, which is a type of bacteria found in the environment. These bacteria frequently get stuck in areas that lack food while swimming well in places where the food is abundant. The movement of the bacterium can be calculated as:

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \quad (4)$$

where $\theta^i(j,k,l)$, represent the *ith* bacterium with *jth* chemotaxis, and *lth* elimination step, $C(i)$ represent the size of the step that taken the random direction and Δ represent the vector that moves in a random direction

2. Swarming: For bacteria to attract an individual to move towards the centre of the population, they generate information to attract them. In the E. Coli swarm, the signals from cell to cell can be represented as:

$$J_{cc}(\theta, P(j,k,l)) = \sum_{i=1}^{s} J_{cc}\left(\theta, \theta^i(j,k,l)\right) = \sum_{i=1}^{s}[-D_{att}\exp(-W_{att}\sum_{m=1}^{P}\left(\theta_m - \theta_m^i\right)^2)]$$
$$+ \sum_{i=1}^{s} H_{rep}\exp(-W_{rep}\exp\sum_{m=1}^{P}\left(\theta_m - \theta_m^i\right)^2)] \quad (5)$$

where $J_{cc}(\theta, P(j,k,l)), P, s, \theta$ indicate the value of the objective function, the variables which need to be optimized, the total number of bacteria, and a point in the search domain of p-dimensional, respectively. The coefficients $D_{att}\ and\ W_{att}$ represent the depth at which the bacteria released the attracted material, and the width of this material, respectively. When the bacteria can not be in the same place, the reputation is taken as $H_{rep},\ and\ W_{rep}$, all these coefficients must be chosen carefully [23].

3. Reproduction: ultimately, to preserve the survival of optimal bacteria, weak bacteria are eliminated and maintain the bacteria that have a strong ability to find food to keep the size of the population. The fitness of the bacterium can be represented as:

$$J_{i,health} = \sum_{j=1}^{N_c} J_i(j,k,l) \quad (6)$$

whereN_c, represent the maximum number of chemotaxis.

4. Elimination-Dispersal: this process has been suggested in the event of bacteria death or its departure to new places or other unexpected situations. When there is a possibility that a

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bacterial individual may die, a new individual will be generated that may differ in its characteristics from the original individual. Still, it can promote the search for the optimal solution.

$$r = random\ [0,1]$$
$$P_i(j,k,l) = \begin{cases} P_i(j,k,l), & r > P_{ed} \\ (m'_1, m'_2, \dots, m'_P, & r > P_{ed} \end{cases} \tag{7}$$

When an optimal solution to a specific problem is required, these bacteria treat one practical solution that is considered a research agent that continues to move on the functional surface until the optimal solution is located [22]. *Fig. 1* and *Fig. 2* illustrate the flow chart and block diagram of the PID tuned by the BFO algorithm.

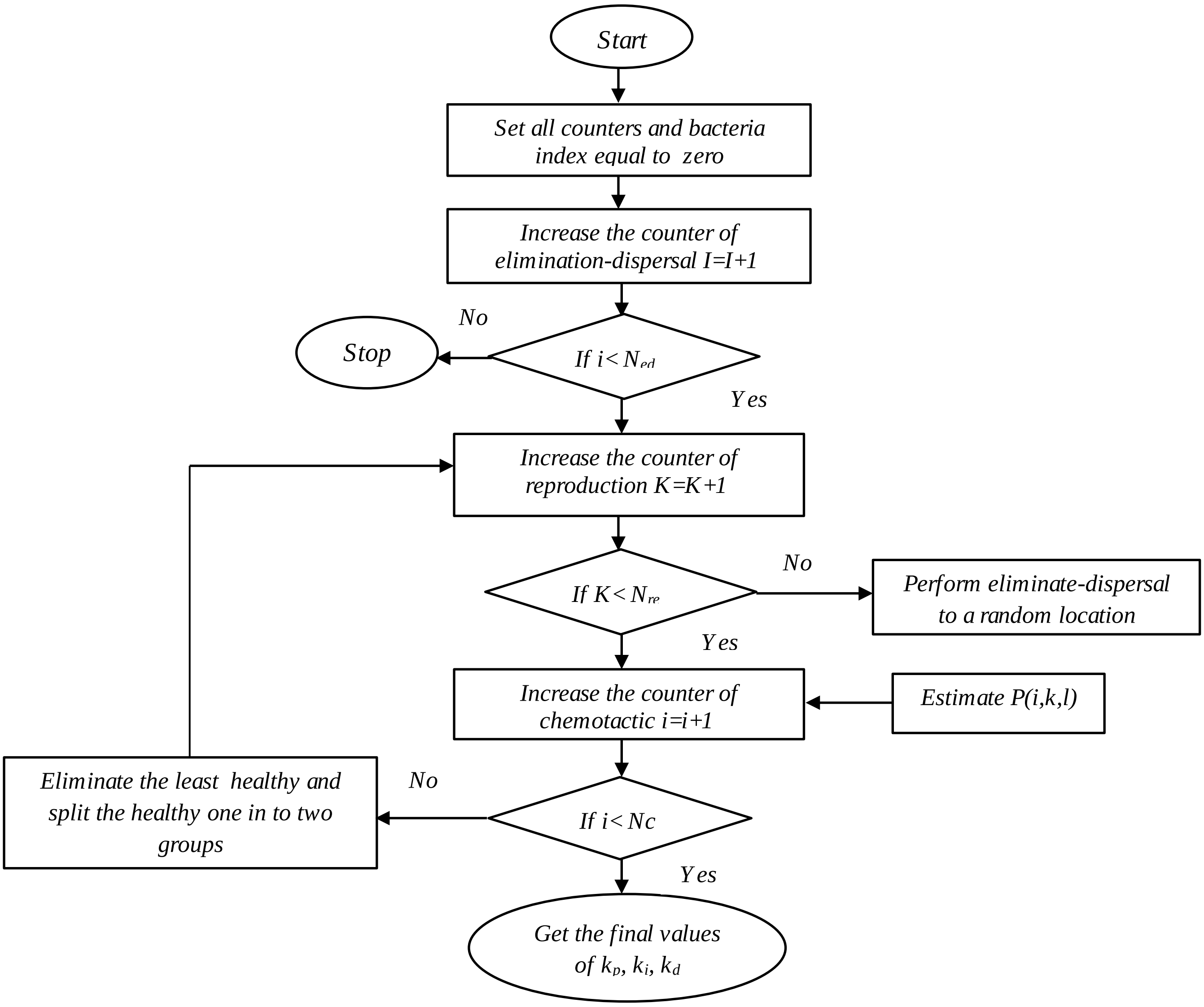

FIG. 1. THE FLOW CHART OF PID TUNING BY THE BFO ALGORITHM.

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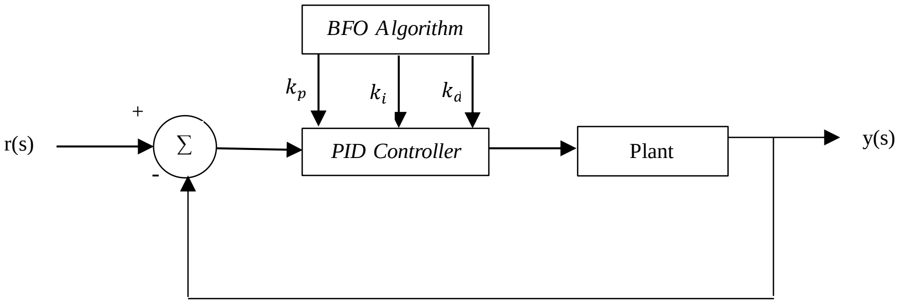

FIG. 2. PID TUNING BY BFO ALGORITHM.

IV. UNKNOWN INPUT OBSERVER

The main objective of UIO is to decouple unknown inputs from the state estimation error [24]. The structure of such an observer is given in Eq. (4) below [25]:

$$\begin{aligned} \dot{z}(t) &= Fz(t) + TBu(t) + Ky(t) \\ \hat{x}(t) &= z(t) + Hy(t) \end{aligned} \tag{8}$$

where: $\hat{x}(t) \in R^n$ and $z(t) \in R^n$ are the estimated state vector and the state of the observer, respectively.

The following equation governs the state estimation error:

$$e(t) = x(t) - \hat{x}(t)$$
$$\dot{e}(t) = \dot{x}(t) - \dot{\hat{x}}(t)$$
$$\dot{e}(t) = (A - HCA - K_1C)e(t) + [F - (A - HCA - K_1C)]z(t) +$$
$$[K_2 - (A - HCA - K_1C)H]y(t) + [T - (I - HC)]Bu(t) + (HC - I)Ed(t) \tag{9}$$

where $Ed(t)$ is the unknown term, and (H, F, K, T) represent the matrices that must be designed in order to attain the unknown input decoupling, the estimating error becomes a function of $Fe(t)$:

$$\dot{e}(t) = Fe(t) \tag{10}$$

where $e(t)$ will asymptotically approach zero if all the eigenvalues of (F) are stable, the matrices of the UIO [F, T, H, and K] are obtained by holding the following equations:

$$(HC - I)E = 0 \tag{11}$$

$$T = I - HC \tag{12}$$

$$F = A - HCA - K_1 \tag{13}$$

$$K_2 = FH \tag{14}$$

$$K = K_1 + K_2 \tag{15}$$

$$K = K_1 + FH \tag{16}$$

Where E is the distributed matrix, and K_1 represent the free matrix to be a design of the UIO. There are some necessary conditions for the UIO:

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- The rank of (CE)=Rank of (E)
- The pair (A_1, C) is detectable, and $A_1 = A - E[(CE)^T CE]^{-1}(CE)^T(CA)$

The block diagram of UIO can be shown in the *Fig. 3*.

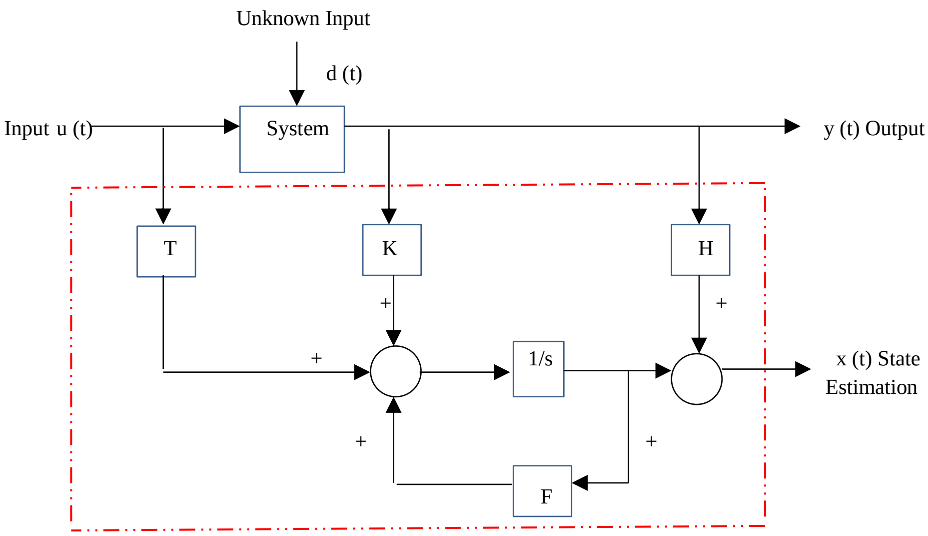

FIG.3. BLOCK DIAGRAM OF UIO.

By using the pole placement, the pair (A_1, C) can be detectable to choose the suitable gain matrix (K_1), and if the pair (A_1, C) is an observer, so the UIO exists.

V. ILLUSTRATIVE EXAMPLE

In large-scale interconnected systems, the type of the controller is an essential issue because of economics, complexity, size, etc. Then the decentralized controller pays attention to a local controller designing for each subsystem [26]. *Fig. 4* indicates the scheme of the observer-based decentralized control with unknown interactions.

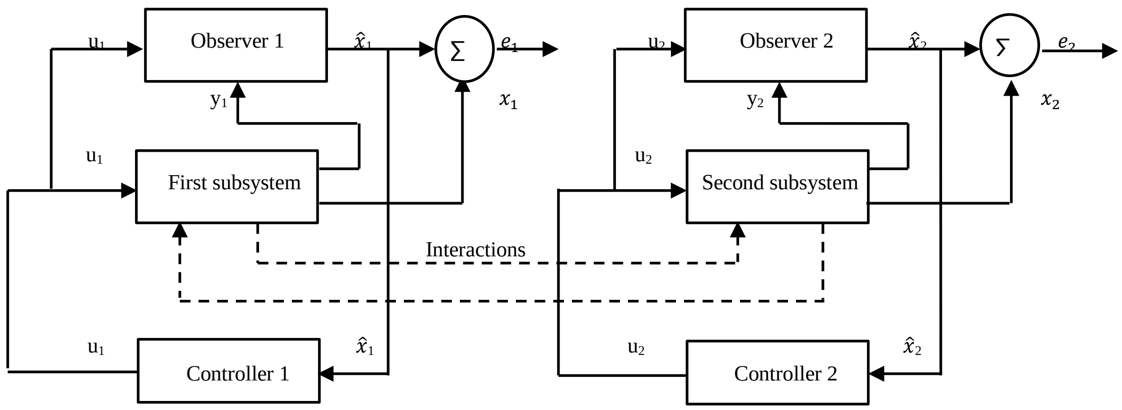

FIG.4. OBSERVER-BASED DECENTRALIZED CONTROL WITH UNKNOWN INTERACTIONS BETWEEN SUBSYSTEMS.

A numerical example was chosen to illustrate the efficiency of the proposed strategy. Assuming that the interconnected system consists of two subsystems with unknown interactions between them [16]:

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$$\dot{x}_1 = \begin{bmatrix} -1 & 5 \\ 0 & -4 \end{bmatrix} x_1 + \begin{bmatrix} 1 \\ 2 \end{bmatrix} u_1 + \begin{bmatrix} 1 & 0 \\ 2 & 0 \end{bmatrix} x_2 + f_1 + E_1 f_{a1} \tag{17}$$

where $x_1 = \begin{bmatrix} x_{11} \\ x_{12} \end{bmatrix}$, $f_1 = \begin{bmatrix} 0 \\ 0.15 \sin(x_{12}) \end{bmatrix}$ is the nonlinear term for the first subsystem, $E_1 = 0$ is the distributed matrix, and $f_{a1} = 0$ (fault-free) represents the actuator fault for the first subsystem. The measured output is:

$$y_1 = [1 \;\; 0] x_1 \tag{18}$$

The second subsystem is:

$$\dot{x}_2 = \begin{bmatrix} -1 & 3 \\ 0 & -3 \end{bmatrix} x_2 + \begin{bmatrix} 1 \\ 1 \end{bmatrix} u_2 + \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix} x_1 + f_2 + E_2 f_{a2} \tag{19}$$

with:

$$y_2 = [1 \;\; 0] x_2 \tag{20}$$

where $x_2 = \begin{bmatrix} x_{21} \\ x_{22} \end{bmatrix}$, $f_2 = \begin{bmatrix} 0 \\ -0.22\sin(x_{22}) \end{bmatrix}$ is the nonlinear matrix for the second subsystem, $E_2 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ is the distributed matrix, and f_{a2} = step fault, which represents the actuator fault for the second subsystem.

The parameters of the BFO algorithm and the PID controller are described in Table I and Table II, respectively.

TABLE I. THE PARAMETERS OF BFO ALGORITHM

The Parameters of BFO	Values
C	10
N_s	2
N_{re}	3
N_c	10
N_{ed}	2
H_{rep}	0.1
W_{rep}	10
W_{att}	0.03
D_{att}	0.01

TABLE II. THE PARAMETERS OF PID CONTROLLER

The parameters of the PID controller	The first subsystem	The second subsystem
k_p	**16.552**	**7.609**
k_i	**77.178**	**77.54**
k_d	**0.103**	**0.0133**

Using MATLAB/SIMULINK, a unit step input in $u_1(t)$ and $u_2(t)$ is set for the simulation study. In a fault-free case, the closed-loop control input for each subsystem is shown in *Fig. 5*.

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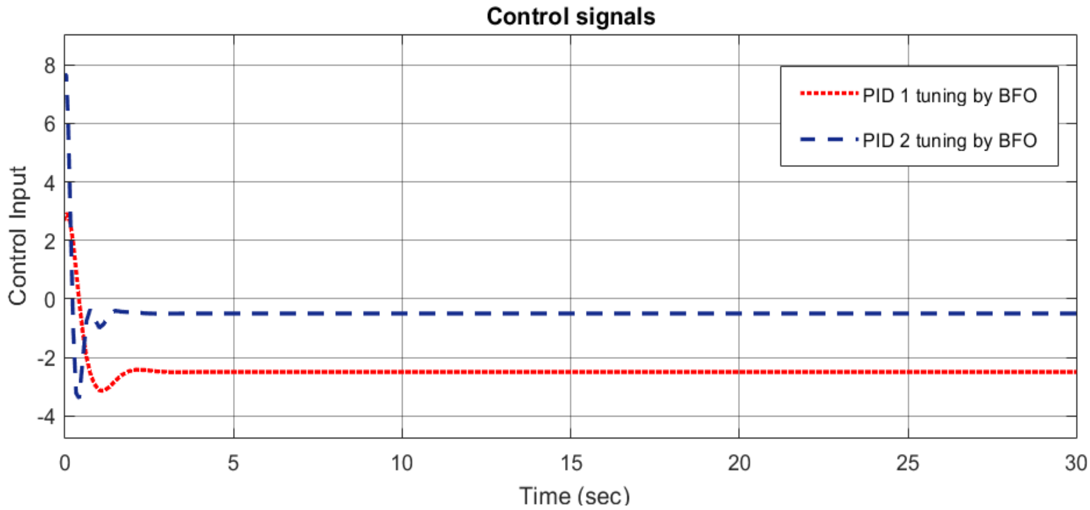
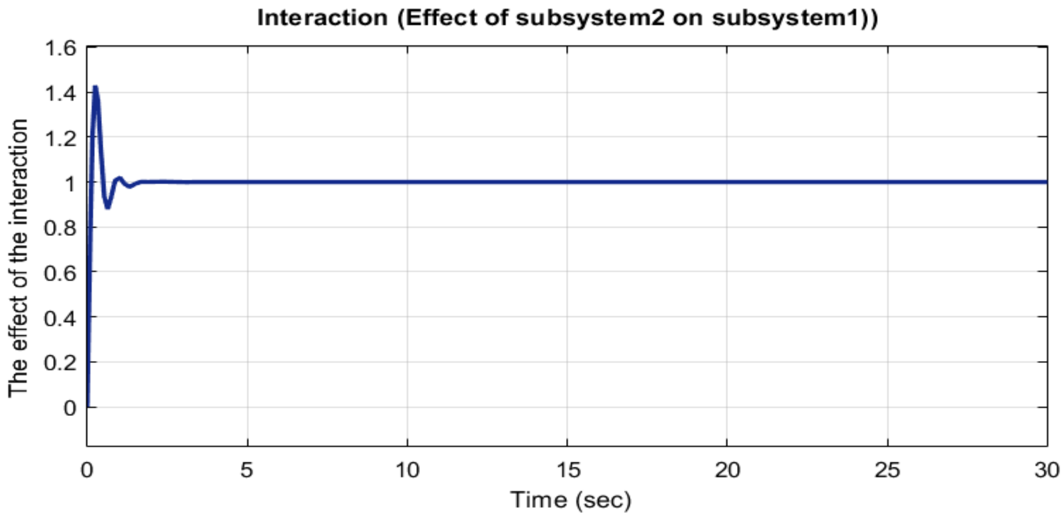
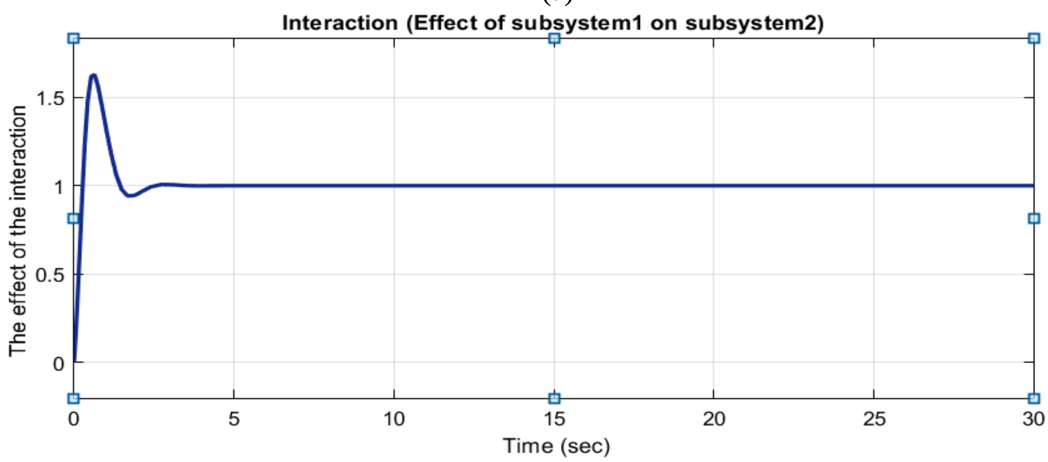


FIG.5. THE CONTROL INPUT OF TWO SUBSYSTEMS.

The influence of the interaction between subsystems is displayed in *Fig. 6*, where *Fig. 6-a* shows the effect of subsystem 2 on subsystem 1, while *Fig. 6-b* shows the effect of subsystem 1 on subsystem 2. *Fig. 6* shows that the two subsystems are stable, indicating that the proposed controller can provide robust stability despite the presence of the interactions.



(a)



(b)

FIG.6. THE INTERACTION BETWEEN SUBSYSTEMS.

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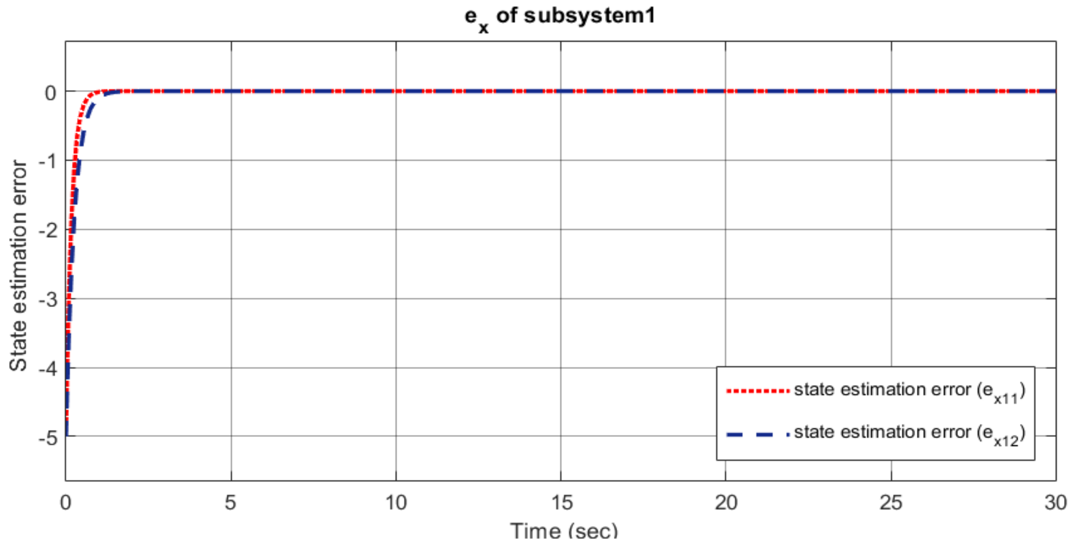
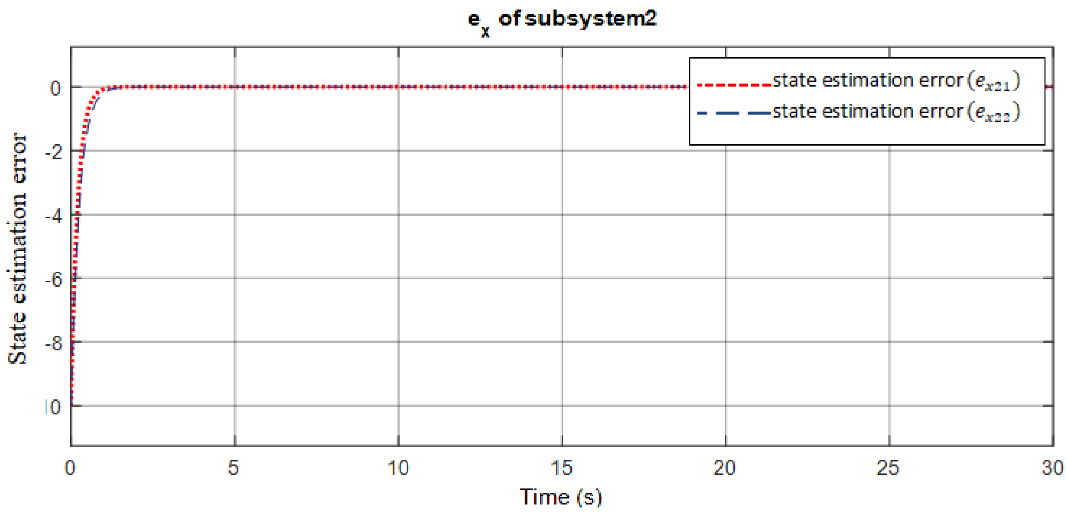
The estimation errors for each subsystem are shown in *Fig. 7*. After using the UIO, the estimation errors for two subsystems asymptotically converge to zero, although the presence of the interactions between them. So, we can conclude that the suggested observer is effective and successful in designing.



(a)



(b)

FIG.7. (a) THE ESTIMATION ERROR OF SUBSYSTEM1 (b) THE ESTIMATION ERROR OF SUBSYSTEM2.

The interaction between subsystems acts as additional disturbance/uncertainty. The effects of these interactions make the fault estimation inaccurate, where most methods of fault diagnosis treaty with only single types of faults. *Fig. 8* shows the actual states of the two subsystems $(x_{11}, x_{12}, x_{21}, x_{22})$ with and without the influence of the interactions.

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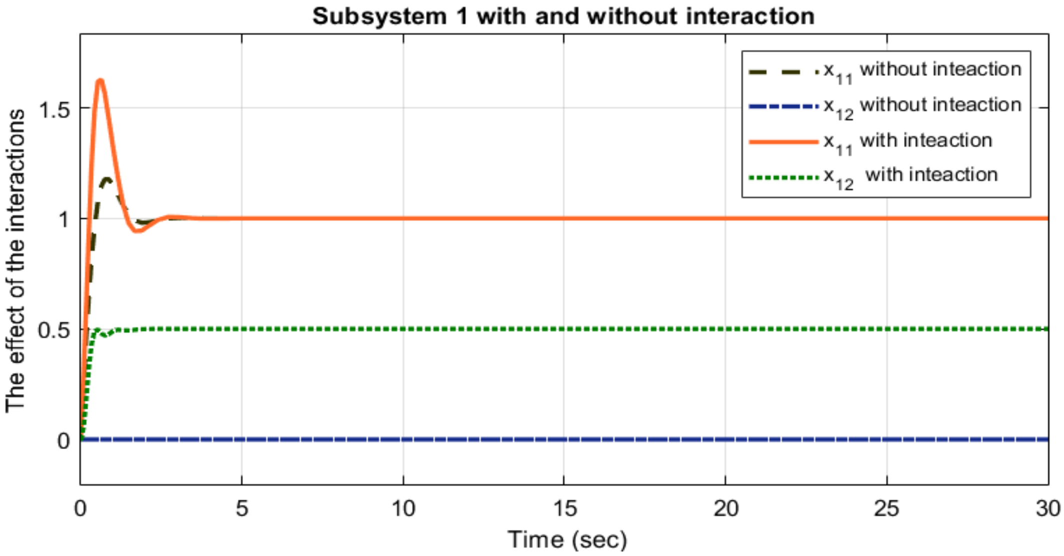
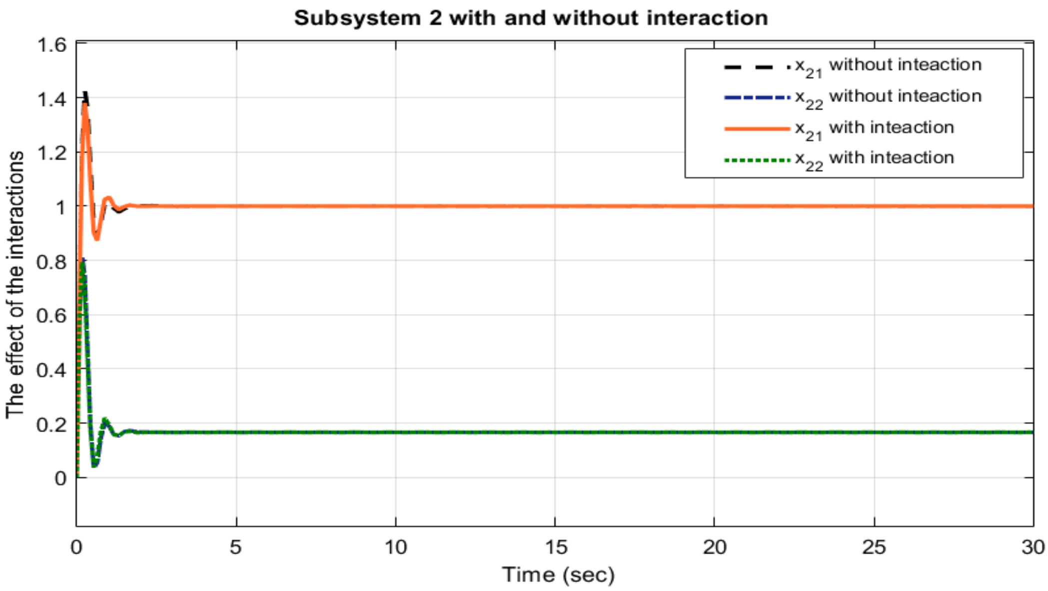


(a)



(b)

FIG.8. (a) THE TIME RESPONSE OF SUBSYSTEM1 (b) THE TIME RESPONSE OF SUBSYSTEM2.

Actuator faults have been added to the second subsystem to demonstrate the given approach's efficiency and assume that the first subsystem is fault-free (note that the actuator fault is a step fault). *Fig. 8* shows the effect of actuator fault on the closed-loop control input for each subsystem. The measured value in subsystem 2 deviates from its normal measurement after 15 seconds when the actuator fault occurs. On the other hand, *Fig. 9* shows how the UIO can detect actuator fault despite the interaction effect.

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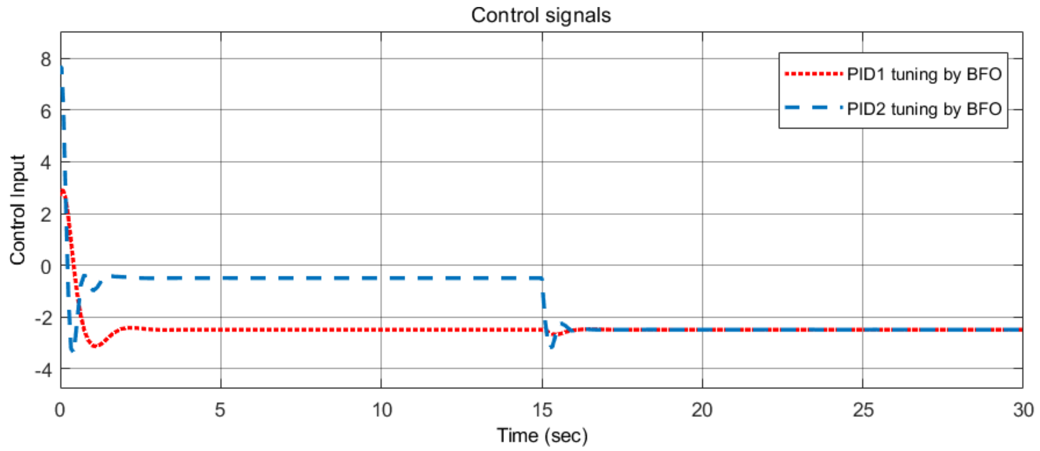

FIG. 9. THE CONTROL INPUT OF TWO SUBSYSTEMS IN THE PRESENCE OF A FAULT ACTUATOR.

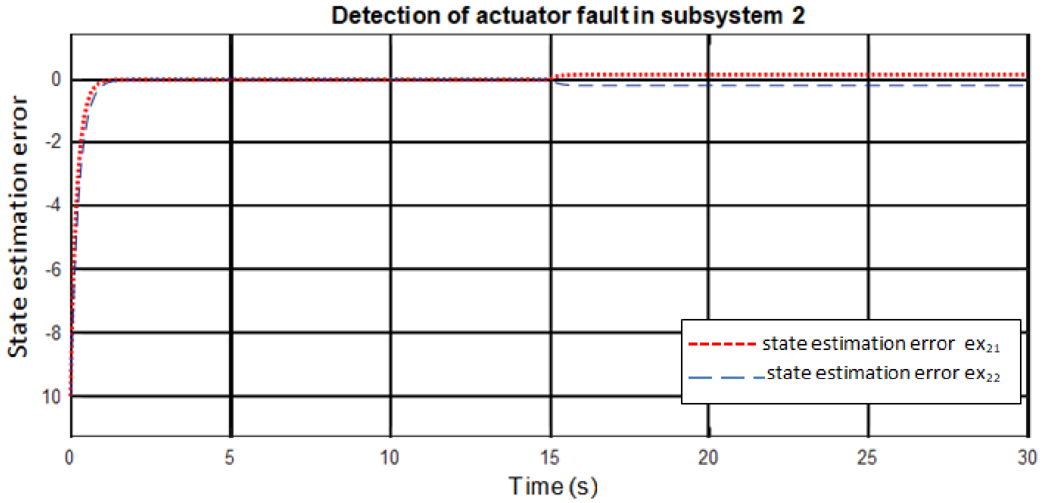

FIG.10. ROBUST ACTUATOR FAULT DETECTION DESPITE THE EFFECT OF SYSTEM INTERACTION.

Fig. 10 illustrates that the state estimation error in the second subsystem converges to zero until the added fault occurs at 15 sec for the two actual states of the subsystem.

In the other case, the previous fault is used with a sine signal added to the second subsystem; the effect of the fault on the closed-loop control input is illustrated in *Fig. 11*.

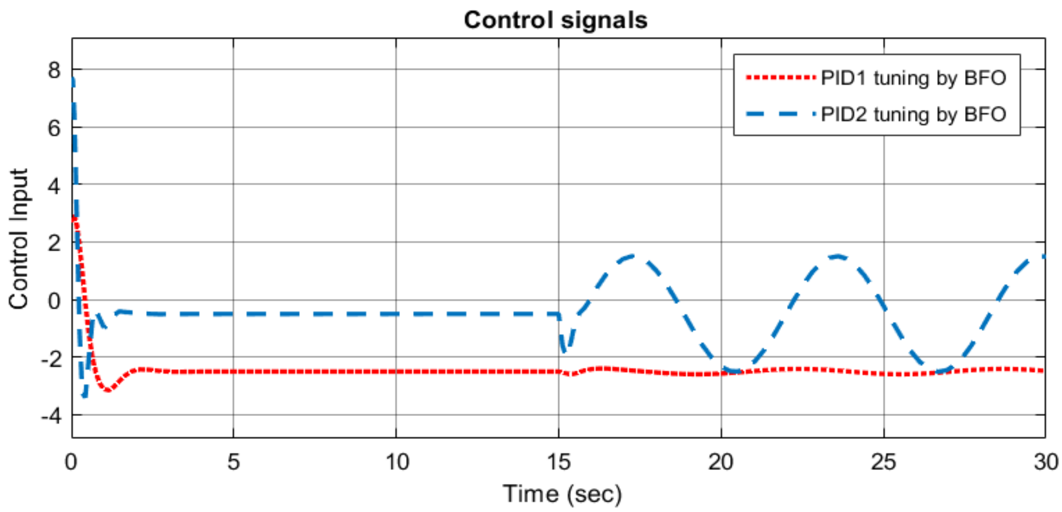

FIG.11. THE CONTROL INPUT OF TWO SUBSYSTEMS IN THE PRESENCE OF A FAULT ACTUATOR.

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The fault occurs at 15 seconds, and the result shows a strong response to the closed-loop system with time-varying described by the sine signal. Hence the need to design fault-tolerant control to compensate for the fault and reduce its impact on the system.

VI. CONCLUSIONS

This article proposes a decentralized controller/observer for nonlinear interconnected systems with actuator fault using robust PID controller tuning by BFO algorithm with UIO. The major advantage of designing the decentralized local controllers is disconnecting the faulty subsystem if the local control reconfiguration is impossible. A numerical example is presented with and without disturbances (interactions and fault) to confirm the robustness and effectiveness of the proposed strategy. For future work, using the FTC system is suggested to compensate for the fault and guarantee the desired performance level after any fault.

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