IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received January 17, 2020, accepted February 1, 2020, date of publication February 10, 2020, date of current version February 18, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2972621

A Neural Network-Based Adaptive Backstepping Control Law With Covariance Resetting for Asymptotic Output Tracking of a CSTR Plant

OBAID ALSHAMMARI[1], MUHAMMAD NASIRUDDIN MAHYUDDIN[1], AND HOUSSEM JERBI[2]

[1]School of Electrical and Electronic Engineering, Engineering Campus, Universiti Sains Malaysia, Nibong Tebal 14300, Malaysia
[2]Engineering College, Industrial Engineering Department, University of Hail, Ha'il 2440, Saudi Arabia

Corresponding author: Muhammad Nasiruddin Mahyuddin (nasiruddin@usm.my)

This work was supported by the Universiti Sains Malaysia (USM), through the USM RCMO Fund and the School of Electrical and Electronic Engineering KPI Fund.

ABSTRACT A robust nonlinear adaptive controller merging a backstepping approach with neural networks is proposed for a nonlinear non-affine model. The work presented here is evaluated on a complex uncertain model of a continuous stirred tank reactor plant including an unknown varying parameter that enters the complexity model. By exploiting NN and adaptive backstepping approximation methods, an equivalent adaptive NN controller is constructed to achieve robust asymptotic output tracking control. The robustness to uncertainties as well as the lack of informative process data is the main enhancement of this work. This is attained through the implementation of the covariance resetting algorithm in the least square estimation of the NN weight tuning algorithm. The proposed novel control algorithm has been analyzed using Lyapunov analysis. In addition to excellent output trajectory tracking performance, the proposed approach has a profound benefit in terms of substantially lower control effort in comparison to the established work in the literature. In terms of applications in the petrochemical industry, lower control effort can translate to a more energy-efficient actuator, leading to lower costs over a long-run operation. The proposed method's feasibility for chemical process control was shown via numerical simulation.

INDEX TERMS Nonlinear non-affine model, Lyapunov theory, backstepping adaptive design, neural network approximation.

NOMENCLATURE

q	CSTR flowrate
$c_{\min}$	Component concentration
T_F	Feed stream temperature
T_{CF}	Inlet fresh coolant temperature
T_A	The reaction temperature
V_T	Total volume of the CSTR
Q_c	Coolant flowrate
ISE	Integral of the square error
IAE	Integral absolute error
CSTR	Continuous stirred tank reactor
NN	Neural network
IFT	Implicit function theorem
MVT	Mean value theorem

The associate editor coordinating the review of this manuscript and approving it for publication was Shihong Ding.

I. INTRODUCTION

Numerous chemical plants such as chemical reactors, distillation columns and water desalination processes can display notable nonlinear behavior. In the case of operating in the neighborhood of nominal steady states, severe impacts of nonlinearities may not persist while satisfactory control performance could be achieved via conventional control schemes with regard to local first-order linearized models. Nevertheless, should a broad range of conditions be handled by the process, traditional linear control techniques fail to manage the system nonlinearities. In such cases, appropriate detuning of controllers ensures closed-loop stability, resulting in losses in the global closed-loop achievements [1], [2]. Recently, the literature has presented numerous interesting results regarding chemical process control [3], [4]. Exact and accurate knowledge of mathematical models of the plant dynamics is needed for most feedback linearization control strategies.

Nonetheless, in general practice, it is complicated to obtain a precise model due to the lack of imminent process parameter data and measurements as well as the inherent complexity of chemical plants. To manage uncertainties and hard model nonlinearities, it is imperative to make use of adaptive approaches ensuring interesting control performance [5]. In [6]–[9], records of many control schemes regarding online scheduling in feedback controller design have been provided, which showed larger achievements when time-varying process parameters and/or uncertainties were present. In this research work, the control issue pertaining to an uncertain nonlinear model of a CSTR, as presented in [10], has been considered. The following state equations define the process dynamics:

$$\begin{cases} \dot{c}_A = \dfrac{q}{V_T}(c_{\min} - c_A) - A_0\, c_A\, e^{(-A_e/T_A)} \\ \dot{T}_A = \dfrac{q}{V_T}(T_F - T_F) + A_0\, c_A\, e^{(-A_e/T_A)} \\ \qquad + A_3 Q_c [1 - e^{(-A_2/Q_c)}](T_{CF} - T_A) \end{cases} \tag{1}$$

The significance and the numerical values of the different parameters of the CSTR model are depicted in Table 1.

TABLE 1. CSTR model parameters and their corresponding significance and values.

	Parameters	Values
CSTR flowrate	q	$100\ l\,/\,min$
Component concentration	$c_{\min}$	$1\ mol\,/\,l$
Feed stream temperature	T_F	$350\ K$
Inlet fresh coolant temperature	T_{CF}	$350\ K$
Total volume of the CSTR	V_T	$100\ l$
Heat transfer coefficient	h_a	$7\ e5\ J\,/\,min\ K$
Preexponential factor	A_0	$7.2\ e10\ min^{-1}$
Activation energy	A_e	$1\ e4\ K$
Heat of reaction constant pressure	$(-\Delta H)$	$2\ e4\ cal\,/\,mol$
Liquid density	ρ_1, ρ_c	$1\ e3\ g\,/\,l$
Heat capacities	c_p, c_{pc}	$1\ cal\,/\,g.K$

TABLE 2. Descriptions of the parameters for the studied CSTR model.

Uncertain parameters	Value and expression
A_1	$(-\Delta H)\, A_0 / \rho_1 c_p = 1.44\,e13$
A_2	$h_a / \rho_c c_{pc} = 6.987\,e2$
A_3	$\rho_c c_{pc} / \rho_1 c_p V_T = 0.01$

Inside the tank reactor, compound A is synthesized by mixing two chemicals for reaction at a mixture temperature of T_A and concentration of c_A. The reaction is characterized as being both exothermic and irreversible. The purpose of the control is to alter the control variable Q_c for regulating the desired output variable c_A. It needs to be noted that the description of the CSTR mentioned above does not match that of conventional reactor control schemes [3], [8]. For a majority of applications, the selection of cooling temperature is chosen as the control input variable and is considered to remain a steady value through the reactor cooling circuit. Selecting Q_c as the manipulated variable offers two key advantages. First, the coolant temperature can be changed along the cooling circuit's length [11]. Should the cooling circuit be lengthy, which is common in practical plants, assuming the coolant temperature to be constant could create a significant approximation in the CSTR modeling. Second, when compared with manipulating the coolant temperature, varying Q_c provides a readily and easily implementable control strategy from a practical point of view. Although simple dynamics are considered to be associated with the CSTR, the model demonstrates the issues faced when controlling such processes. It needs to be noted that the developed techniques in the literature can be implemented for large chemical reactors.

In this research work, the developments are limited to the particular described dynamics (1) to offer a straightforward case for the presented approach. The key difficulty faced in the present control issue is that a common affine system control input is not assumed by the plant since the control input Q_c tends to exhibit nonlinearity. If the plant model is well defined, for a wide category of nonlinear non-affine systems, input-output linearization control was evaluated in [2]. [12] and [13] investigated the implementation pertaining to an online control design for uncertain nonlinear models based on an adaptive learning method. To show the benefits of employing learning and adaptation, control implementation for CSTR models was given in [14], [15]. Nevertheless, a thorough stability investigation was missing for the global control design because of high complexity associated with neural network systems [12], [13], [16], [17]. Measuring the time derivative of c_A is needed for the scheme given in [10], whose estimation is difficult. In reality, the literature demonstrates numerous studies that have recommended the implementation of NNs as potent structures to control the class of complex nonlinear models [18], [19]. Moreover, the efficiency of NN controllers has been extensively justified, particularly when the model information is lacking or even when a controlled process is characterized by model parameter uncertainties [20].

In fact, the most valuable feature of NNs is their ability to approximate any nonlinear function without complete knowledge of the plant model structure. Thus, NNs are characterized by a dynamic representation that provides satisfactory control achievements in the case of unmodeled plant dynamics [21], [22]. The fundamental concepts in NN-based controllers are to offer online learning structures that do not necessitate initial offline adjustment. Some of these learning structures have been established from the Lyapunov stability theory [23]–[26]; however, some other algorithms were inspired by backpropagation learning algorithms [27], [28]. On the other hand, several works have been dedicated to backstepping control design for parametric uncertain nonlinear models [29], [30]. This latter approach can be efficiently implemented to linearize hard system nonlinearities in the existence of modeling uncertainties [31], [32]. Its basic concept consists of selecting recursive proper functions for a state variable subcontrol law for subsets of reduced dimension regarding the global system. Every backstepping step outcome is a new subcontrol scheme, stated in the form of a new pseudocontrol input from previous synthesized steps. The design includes a feedback-based scheme for the system input variable, which attains the pertaining performance based on the Lyapunov stability theory [33]. Recently, there has been an important amount of research activities in the field of adaptive control for nonlinear systems exploiting the feedback linearization formalism [34], [35]. The main assumption in these works is that the plant under investigation is affine in control variable, i.e., from the point of view of control inputs, the plant model is linear, and the nonlinearities are linearly parameterized. Nonetheless, several real plants with chemical reactors are characterized by inherent nonlinearities, whose manipulated variables may not be defined in an affine form. In this situation, feedback linearization techniques are not applicable, motivating us to resort to creating a virtual controller via an adaptive backstepping technique.

The most challenging constraints for the investigated control problem are two-fold: First, selecting Q_c as the manipulated variable compels the control input to evolve with only a positive sign, implying that the coolant flows in only one direction toward the coolant jacket, i.e., irreversible flow. Second, the dynamics of the desired output submit a hard constraint, as the output c_A has been characterized by a step variation along the input reference of $\pm 0.02\ mol/l$ as well as a suitable concentration value of $0.1\ mol/l$. Moreover, the concentration cannot exceed $1\ mol/l$. Overcoming these two constraints while achieving the output tracking of the studied CSTR model with accurate nonoscillatory behavior is considered one of the main contributions of this work. In this paper, the investigation of a robust backstepping adaptive control method for a CSTR plant (1) is evaluated. To derive the control strategy, the method integrates a Lyapunov stability design with neural network modeling and adaptive backstepping control. The robustness against uncertainties, which is the main enhancement of this work, is attained through an implementation of the covariance resetting algorithm in the least square estimation of the NN weight tuning algorithm. Section II of this paper provides some of the notation as well as the theoretical background. Section III presents the main developments of robust adaptive backstepping design. Addressing both the control performance and stability pertaining to closed-loop systems is performed. Section IV provides the numerical simulation results to display the efficiency of the proposed approach. Concluding remarks are provided in the last section.

II. PROBLEM DESCRIPTION

In this research work, nominal values of the CSTR process parameters ($V_T, T_{CF}, q, c_{\min}$, and T_F) are assumed, as described in Table 1. Let us state the state variable representation expressed by $x = [x_1, x_2]^T = [c_A, T_A]^T$ and $y = c_A$. The description of the CSTR plant is:

$$\begin{cases} \dot{x}_1 = 1 - x_1 - A_0 x_1\, e^{-1e4/x_2} \\ \dot{x}_2 = T_F - x_2 + A_1 x_1\, e^{-1e4/x_2} \\ \qquad + A_3 u(1 - e^{-A_2/u}(T_{CF} - x_2) \\ y = x_1 \end{cases} \tag{2}$$

It needs to be emphasized that constant parameters (A_i, $i = 0, \ldots, 3$) represent the unknown parameters, subject to uncertainties in the studied CSTR model. The aim of this work is to develop a control law u to track the real system output y toward a selected signal y_d. Two main problems are faced by the control design. First, the uncertain parameter represented as A_2 is seen as nonlinear in the second equation of the plant model (2). Due to this, conventional identification and estimation techniques cannot be exploited for accurate determination of A_2. Second, the manipulated variable is seen as nonlinear and non-affine in equation (2) of the model. Even though this cannot be regarded as a major shortcoming for the design of a control strategy, a more cautious analysis is needed here instead of backstepping-based control and feedback linearization formalism. This research work proposes a novel control strategy to address the advanced robust tracking control issue for nonlinear non-affine models that face related types of structural modeling complications [36].

III. ADAPTIVE BACKSTEPPING-BASED CONTROL DESIGN

To start, some important assumptions are stated for the developments in this section.

Assumption 1: The CSTR's state variables operate in the set Ω_x under the following constraints:

$$\begin{cases} x_1 \in [c_{\min} \quad 0.12] \\ x_2 \in [T_{\min} \quad T_{\max}] \\ u \in [0 \quad u_0] \end{cases} \tag{3}$$

wherein $T_{\min}$ is the lower bound of the tank temperature and $c_{\min}$ is the minimal considered value of the product concentration.

Assumption 2: The uncertain parameters ($A_i, i = 0, \ldots, 3$) are assumed to be bounded by constant known parameters as follows:

$$\begin{cases} A_0 \leq A_{0\max} \\ A_1 \leq A_{1\max} \\ A_2 \geq A_{2\min} \\ A_3 \geq A_{3\min} \end{cases} \tag{4}$$

Assumption 3: The desired reference input y_d and its derivatives $\dot{y}_d$, $\ddot{y}_d$ and $y_d^{(3)}$ belong to an unknown compact set $\Omega_d \subset \mathbb{R}^4$.

In recent literature [37], [38], a known backstepping adaptive control law was further designed for a broader nonlinear systems class. The triangular structure needed for the backstepping design is satisfied by model (2). Indeed, the nonlinear quantity

$$A_o x_1 e^{-1e4/x_2} \tag{5}$$

can be considered inner control for the first model state variable x_1. Then, the second state variable x_2 can be controlled based on the manipulated variable u letting the quantity in (5) be compelled to attain the control objectives. The backstepping design investigated in this work is performed based on the changes in the following variables:

$$\begin{cases} z_1 = x_1 - y_d \\ z_2 = x_1 e^{-1e4/x_2} - \alpha_1 \end{cases} \tag{6}$$

where α_1 is a smooth function to be designed later. By merging equations (2) and (6), it is easy to obtain:

$$\dot{z}_1 = 1 - \dot{y}_d - A_0(\alpha_1 + z_2) - x_1 \tag{7}$$

Let us define the positive definite Lyapunov function given by:

$$V_1 = \frac{z_1^2}{2A_0} \tag{8}$$

For equation (8), its time derivative is:

$$\dot{V}_1 = z_1\left[\frac{1}{A_0}(1 - x_1 - \dot{y}_d) - (z_2 + \alpha_1)\right] \tag{9}$$

Thus, selecting α_1 as

$$\alpha_1 = \hat{\theta}_1(1 - x_1 - \dot{y}_d) + k_1 z_1 \tag{10}$$

leads to the following:

$$\dot{V}_1 = -z_1(k_1 z_1 + z_2) - \left(\hat{\theta}_1 - \theta_1^*\right)(1 - x_1 - \dot{y}_d) \tag{11}$$

where $\hat{\theta}_1$ is the estimator of the uncertain parameter A_0 that can be written as $\hat{\theta}_1 = \theta_1^* - 1/A_0$ and k_1 is a positive constant.

Let us denote:

$$\begin{cases} \tilde{\theta}_1 = \hat{\theta}_1 - \theta_1^* \\ V_{s1} = V_1 + \dfrac{\tilde{\theta}_1^2}{2\gamma_1} \quad \textit{with } \gamma_1 > 0 \end{cases} \tag{12}$$

Differentiating V_{s1} allows obtaining an adaptive law given by:

$$\dot{\hat{\theta}}_1 = -\delta_s\hat{\theta}_1 + \gamma_1(1 - x_1 - \dot{y}_d) \tag{13}$$

and thereafter:

$$\dot{V}_{s1} = -\left[\frac{\delta_s}{\gamma_1}\tilde{\theta}_1\hat{\theta}_1 + z_1(k_1 z_1 + z_2)\right] \tag{14}$$

It should be noted that $\delta_s\hat{\theta}_1$ is a leakage term that has been characterized by the constant $\delta_s > 0$ and was associated with the adaptive law (13); this is comparable to the σ-modification learning control input that was developed in [39] to enhance the robustness of the adaptive controlled systems.

From equations (2), (6), and (10), the following is obtained:

$$\dot{z}_2 = \eta_1(\psi) - A_3\eta_2(x)l(u) \tag{15}$$

where $\psi = \begin{bmatrix} x_1 & \hat{\theta}_1 & y_d & \dot{y}_d & \ddot{y}_d & z_2 \end{bmatrix}^T$.

$$\begin{cases} \bullet\ \eta_1(\psi) = \dot{x}_1 e^{-1\ e4/x_2} + \dfrac{1e4\ x_1}{x_2^2}e^{-1e4/x_2} \\ \qquad \left(T_F - x_2 + A_1 x_1 e^{-1\ e4/x_2}\right) - k_1\dot{z}_1 \\ \qquad - \hat{\theta}_1(1 - x_1 - \dot{y}_d) + \hat{\theta}_1(\dot{x}_1 + \ddot{y}_d), \\ \bullet\ \eta_2(x) = \dfrac{\text{le}\,4\ x_1}{x_2^2}e^{-1\ e4/x_2}(x_2 - T_{CF}), \\ \bullet\ l(u) = u\left(1 - e^{-A_2/u}\right) \end{cases}$$

Based on the defined operating region characterized by system (3) and according to assumption 2, that the following is obtained:

$$\begin{cases} \dfrac{\partial l(u)}{\partial u} = 1 - e^{-A_2/u} - \dfrac{A_2}{u}e^{-A_2/u}, \\ \dfrac{\partial^2 l}{\partial u^2} = \dfrac{-A_2^2}{u^3}e^{-A_2/u} \end{cases} \tag{16}$$

which can be bounded by:

$$\begin{cases} \dfrac{\partial l(u)}{\partial u} \geq b_0 \\ \left|\dfrac{\partial^2 l(u)}{\partial u^2}\right| \leq b_1 \end{cases} \tag{17}$$

where b_0 and b_1 are positive coefficients and given by:

$$\begin{cases} b_0 = 1 - e^{-A_{2\min}/u_0} \\ \qquad - (A_{2\min}/u_0)e^{-A_{2\min}/u_0} \\ b_1 = \dfrac{73.386}{A_{2\min}} \end{cases} \tag{18}$$

Note that also according to the operating region (3), it is easy to conclude that:

$$0 < \eta_{2\min} \leq \eta_2(x) \leq \eta_{2\max}, \tag{19}$$

where $\eta_{2\min}$ and $\eta_{2\max}$ are defined by:

$\eta_{2\min} = \inf_{x\in\Omega_x}\{\eta_2(x)\}$ and $\eta_{2\max} = \sup_{x\in\Omega_x}\{\eta_2(x)\}$, respectively.

Remark 1: There exists a control input u such that when $u = \rho(\psi)$, then

$$f_2(\psi, x) = 0, \tag{20}$$

where $f_2(\psi, x) = \eta_1(\psi) - A_3\eta_2(x)\,l(\rho(\psi))$ and (20) holds within a finite set of time intervals $[t_1, t_2, t_i, \ldots, t_n]$ at any arbitrary initial time as long as the function $\rho(\psi)$ is differentiable and continuous, which leads to the condition defined in (16). Let a vector function φ be defined as follows:

$$\varphi = \frac{\partial[\eta_1(\psi) - A_3\eta_2(x)l(u)]}{\partial u}. \tag{21}$$

Then, there exists a function u that is qualified to be regarded as a *sufficiently rich* (SR) signal [39], such that the following condition holds:

$$\int_{t_i}^{t_f} \varphi(r)\varphi(r)^T dr \geq I\upsilon \geq 0, \tag{22}$$

where $r(\psi, x, u) \in \mathbb{R}^k \times \mathbb{R}^n \times \mathbb{R}^p \to \mathbb{R}^n$, υ is a large enough positive constant and $I \in \mathbb{R}^{n\times n}$ is the identity matrix. The condition in (22) is also well known as a *persistent excitation* condition, or PE, as defined in [39].

Remark 2: Let $f_1(\psi, x, u) = \eta_1(\psi) - A_3\eta_2(x)\, l(u)$; then, invoking IFT as expounded in [39], [40] and followed by MVT in [41], [42],

$$f_1(\psi, x, u) - f_2(\psi, x, \rho) = (u - \rho)f'_{u_\lambda} \tag{23}$$

where $f'_{u_\lambda} = \left.\frac{\partial f(\psi,x,u)}{\partial u}\right|_{u=u_\lambda}$ with $u_\lambda = \lambda u + (1-\lambda)\rho$, where $\lambda \in \{0, 1\}$. From the IFT, there exists a unique and ideal continuous control $\rho = U \in \Omega_\rho \subset \mathbb{R}^+$ such that $f_2(\psi, x, \rho) = f_2(\psi, x, U) = 0$ for all $\psi \in \Omega_\psi \subset \mathbb{R}^k$, $x \in \Omega_x \subset \mathbb{R}^n$, where Ω_i, $i \in \{\rho, \psi, x\}$ is used to denote the compact set. Using this notation, (23) can be further rewritten as

$$\begin{aligned} f_1(\psi, x, u) &= f_2(\psi, x, \rho) + (u - \rho)f'_{u_\lambda} \\ &= (u - \rho)f'_{u_\lambda} \end{aligned} \tag{24}$$

Hence, using the result from (24) and the notation undertaken in **Remark 1** and **Remark 2,** the error equation in (15) can be written as:

$$\dot{z}_2 = -A_3 f'_{u_\lambda}\eta_2(x)[u - \rho(\psi)] \tag{25}$$

Proposition 1: The state equation in (25) can be transformed from a non-affine to an affine form by a technique reported in Lemma 3 of [40] where a 2-stage affinity transformation is employed. Let $\hat{u} = u - \rho$ be the universal control input embedding the tracking control and the approximator to be designed later. A lumped function is proposed as follows:

$$\breve{h}(x, \hat{u}) = -A_3 f'\eta_2(x)\hat{u} \tag{26}$$

Invoking the MVT, (26) can be rewritten as

$$\breve{h}(x, \hat{u}) = \breve{h}(x, \hat{\hat{u}}) + (\hat{u} - \hat{\hat{u}})\frac{\partial \breve{h}(x, \hat{u})}{\partial \hat{u}} \tag{27}$$

There exists a unique and continuous universal control input $\hat{\hat{u}} \in \Omega_{\hat{u}} \subset \mathbb{R}$ such that $\breve{h}(x, \hat{\hat{u}}) = 0$ for all $x \in \Omega_x \subset \mathbb{R}^n$. Subsequently, (27) can be further simplified to,

$$\begin{aligned} \breve{h}(x, \hat{u}) &= (\hat{u} - \hat{\hat{u}})\frac{\partial \breve{h}(x, \hat{u})}{\partial \hat{u}} \\ &= -k\hat{u} + \left(\frac{\partial \breve{h}(x, \hat{u})}{\partial \hat{u}} + k\right)\hat{u} - \frac{\partial \breve{h}(x, \hat{u})}{\partial \hat{u}}\hat{\hat{u}} \end{aligned} \tag{28}$$

Thus, (25) can be rewritten as

$$\begin{aligned} \dot{z}_2 &= -k\hat{u} + \left(\frac{\partial \breve{h}(x, \hat{u})}{\partial \hat{u}} + k\right)\hat{u} - \frac{\partial \breve{h}(x, \hat{u})}{\partial \hat{u}}\hat{\hat{u}} \\ &= -ku + k\rho + \left(\frac{\partial \breve{h}(x, \hat{u})}{\partial \hat{u}} + k\right)\hat{u} - \frac{\partial \breve{h}(x, \hat{u})}{\partial \hat{u}}\hat{\hat{u}} \end{aligned} \tag{29}$$

Furthermore, the nonlinear function $n(x, \hat{\hat{u}}) = k\rho + \left(\frac{\partial \breve{h}(x,\hat{u})}{\partial \hat{u}} + k\right)\hat{u} - \frac{\partial \breve{h}(x,\hat{u})}{\partial \hat{u}}\hat{\hat{u}}$ can be approximated with the help of the HONN approximator so that (29) can be expressed as,

$$\dot{z}_2 = -ku + n(x, \hat{\hat{u}}) \tag{30}$$

The approach adopted in this paper is to construct an approximator for function $n(x, \hat{\hat{u}})$ such that (20) holds. The function $n(x, \hat{\hat{u}})$ is assumed to be *linear-in-parameter*, or in a technical sense, it can be linearly parameterized as follows:

$$n(\cdot) = W^{*T}F(\vartheta) \tag{31}$$

where $F(\vartheta)$ is the regressor basis function comprising $\vartheta = [\psi, \hat{u}]$, W^{*T} is the corresponding weightage gain to the basis and ε_l is the approximation error. The weightage gain W can be estimated such that $\hat{W} \to W^*$ by various adaptive laws in the control literature [43]–[45]. In this paper, we intend to exploit a high-order neural network as in [46] and augment the adaptation law with a covariance resetting feature. Based on the selected approximator, the basis vector $F(\vartheta) = [f_1(\vartheta), f_2(\vartheta), \ldots f_l(\vartheta)]^T \in R^l$ is taken. The basis functions are defined as:

$$f_i(\vartheta) = \prod_{j\in I_i}[f(\vartheta)]^{d_j(i)}, \quad i = 1, 2, \ldots l,$$

$$\text{with } f(\vartheta_j) = \frac{\vartheta}{\sqrt{1+\vartheta^2}} \tag{32}$$

where $\{I_1, I_2, \ldots, I_l\}$ can be defined as a gathering of l disordered subsets pertaining to $\{1, 2, \ldots 6\}$ and $d_j(i)$ that are nonnegative integers.

$$\hat{n}(x, \hat{\hat{u}}) = \hat{W}^T F(\vartheta) + \varepsilon_l \tag{33}$$

Consider the control law described by:

$$u = \mu z_2 + \frac{1}{k}\hat{W}^T F(\vartheta) + \frac{1}{k}\xi\, sign(z_2) \tag{34}$$

where $\xi > 0$, $\mu > 0$ and $k > 0$ are the design constants and $\hat{W}$ can be defined as the estimation of W^* selected to fulfill $\| \hat{W} \| \leq w_m$ when designing the adaptive control. Substituting (34) into (30) would yield

$$\dot{z}_2 = -k\mu z_2 - \tilde{W}^T F(\vartheta) - \xi\ sign(z_2) - \varepsilon_l \tag{35}$$

Theorem 1: Consider the nonlinear non-affine system described in (2). If the adaptive backstepping neural network controller is designed as in (34) in which the adaptive control input is designed as in (13) and the neural network tuning algorithm is described by:

$$\dot{\hat{W}} = \gamma_2\phi z_2 - \gamma_2^2\hat{W} \tag{36}$$

where $\phi = F(\vartheta)$ for notation brevity,

$$\dot{\gamma}_2 = \mu_0\gamma_2 - \gamma_2\phi\phi^T\gamma_2/m^2 \tag{37}$$

where μ_0 is a positive constant; $m^2 = 1 + n_s^2$; $n_s^2 = m_s$; $\dot{m}_s = -\delta m_s + u^2 + y^2$ when parameter $\gamma_2(t) > 0$ as well as initial condition $\left\|\hat{W}(0)\right\| \leq w_m$; and δ is a positive constant. The covariance matrix $\gamma_2(t)$ has elements that are discontinuous functions of time, whose values are obtained by differentiating the function given in (37). At the point of discontinuity, t^*,

$$\frac{d}{dt}\left(\gamma_2(t^*)\right) \geq 0, \quad i.e.\ \gamma_2^{-1}(t_2) - \gamma_2^{-1}(t_1) \geq 0. \quad \forall t_2 \geq t_1 \geq 0, \tag{38}$$

It should be noted that

$$\gamma_2^{-1}(t) \geq r_0^{-1}\, \mathrm{I}_l, \quad \forall t \geq 0. \tag{39}$$

$$r_0\, \mathrm{I}_l \geq \gamma_2(t) \geq r_1\, \mathrm{I}_l \tag{40}$$

$$r_1^{-1}\, \mathrm{I}_l \geq \gamma_2^{-1}(t) \gg r_0^{-1}\, \mathrm{I}_l \quad \forall t \geq 0 \tag{41}$$

where $r > 0$.

Proof: Define the following positive definite function:

$$V_w(\tilde{W}) = \frac{\tilde{W}^T\gamma_2^{-1}\tilde{W}}{2} \tag{42}$$

where γ_2 is given as in (37) and $\tilde{W} = W - \hat{W}$ is the estimation error vector. As shown and motivated in (40) and (41), $\gamma_2^{-1}(t)$ is a bounded and positive definite symmetric matrix. We may differentiate (42) as follows:

$$\dot{V}_w = \frac{1}{2}\tilde{W}^T\frac{d}{dt}\left[\gamma_2^{-1}\right]\tilde{W} + \frac{d}{dt}\left[\frac{1}{2}\tilde{W}^T\gamma_2^{-1}\tilde{W}\right] \tag{43}$$

$$\begin{aligned}\dot{V}_w &= \frac{1}{2}\tilde{W}^T\frac{d}{dt}\left[\gamma_2^{-1}\right]\tilde{W} + \frac{1}{2}\dot{\tilde{W}}^T\gamma_2^{-1}\tilde{W} + \frac{1}{2}\tilde{W}^T\gamma_2^{-1}\dot{\tilde{W}}\\ &= \frac{1}{2}\tilde{W}^T\frac{d}{dt}\left[\gamma_2^{-1}\right]\tilde{W} + \tilde{W}^T\gamma_2^{-1}\dot{\tilde{W}}\end{aligned} \tag{44}$$

knowing that $\dot{\tilde{W}} = \dot{W} - \dot{\hat{W}} = -\dot{\hat{W}}$ due to $\dot{W} = 0$,

$$\dot{V}_w = \frac{1}{2}\tilde{W}^T\frac{d}{dt}\left[\gamma_2^{-1}\right]\tilde{W} + \tilde{W}^T\gamma_2^{-1}\left[-\dot{\hat{W}}\right] \tag{45}$$

Knowing that the matrix identity in [37] has the following form:

$$\frac{d}{dt}\left[\gamma_2\right]\gamma_2^{-1} + \gamma_2\frac{d}{dt}\left[\gamma_2^{-1}\right] = \frac{d}{dt}\left[\gamma_2\gamma_2^{-1}\right] = 0 \tag{46}$$

and consequently,

$$\frac{d}{dt}\left[\gamma_2^{-1}\right] = -\gamma_2^{-1}\dot{\gamma}_2\gamma_2^{-1} \tag{47}$$

It follows for the identity,

$$\dot{V}_w = \frac{1}{2}\tilde{W}^T\left[-\gamma_2^{-1}\dot{\gamma}_2\gamma_2^{-1}\right]\tilde{W} + \tilde{W}^T\gamma_2^{-1}\left[-\dot{\hat{W}}\right] \tag{48}$$

To guarantee V_W in (48) decreases, we let

$$\dot{\gamma}_2 = -\frac{\gamma_2\phi\phi^T\gamma_2}{m^2} + \mu_0\gamma_2 \tag{49}$$

and

$$\dot{\hat{W}} = -\gamma_2\phi z_2 - \gamma_2^2\hat{W} \tag{50}$$

such that

$$\begin{aligned}\dot{V}_w = &\frac{1}{2}\tilde{W}^T\left[\frac{\phi\phi^T}{m^2}\right]\tilde{W} - \frac{1}{2}\mu_0\gamma_2^{-1}\tilde{W}^T\tilde{W}\\ &+ \tilde{W}^T\gamma_2^{-1}\left[\gamma_2\phi z_2\right]\\ &+ \tilde{W}^T\gamma_2^{-1}\left[\gamma_2^2\hat{W}\right]\end{aligned} \tag{51}$$

$$\begin{aligned}\dot{V}_w = &\frac{1}{2}\frac{\tilde{W}^T\phi\phi^T\tilde{W}}{m^2} - \frac{1}{2}\mu_0\gamma_2^{-1}\tilde{W}^T\tilde{W}\\ &+ \tilde{W}^T\phi z_2\\ &+ \gamma_2\tilde{W}^T\hat{W}\end{aligned} \tag{52}$$

Taking $\hat{W} = W - \tilde{W}$ yields

$$\begin{aligned}\dot{V}_w = &\frac{1}{2}\frac{\tilde{W}^T\phi\phi^T\tilde{W}}{m^2} - \frac{1}{2}\mu_0\gamma_2^{-1}\tilde{W}^T\tilde{W}\\ &+ \tilde{W}^T\phi z_2\\ &+ \gamma_2\tilde{W}^T W - \gamma_2\tilde{W}^T\tilde{W}\end{aligned} \tag{53}$$

Using the Cauchy-Schwarz inequality for the term $\gamma_2\tilde{W}^T W < \frac{\gamma_2}{4}\tilde{W}^T\tilde{W} + \frac{\gamma_2}{4}W^T W$ and consequently, taking the upper bound of (53) as follows:

$$\begin{aligned}\dot{V}_w \leq &\frac{1}{2}\Phi_m\left\|\tilde{W}\right\|^2 - \frac{1}{2}\mu_0\sigma_{\min}(\gamma_2^{-1})\left\|\tilde{W}\right\|^2\\ &+ \left\|\tilde{W}\right\|\|\phi\|\, z_{2m}\\ &- \frac{3}{4}\sigma_{\min}(\gamma_2)\left\|\tilde{W}\right\|^2 + \frac{1}{4}\sigma_{\max}(\gamma_2)\|W\|^2\end{aligned} \tag{54}$$

where $\Phi_m = \|\phi\phi\|_F/m^2$ in particular is the bound of regressor matrix multiplication defined by the Frobenius norm and W is a true value of the parameter estimates, i.e., a constant. Next, we proceed in the analysis by denoting the following positive definite function:

$$\bar{V} = V_2 + V_w = \frac{1}{2}z_2^2 + \frac{1}{2}\tilde{W}^T\gamma_2^{-1}\tilde{W} \tag{55}$$

Taking the derivative of (55) yields

$$\dot{\bar{V}} = z_2\dot{z}_2 + \dot{V}_w \tag{56}$$

and then one has the following:

$$\begin{aligned}\dot{\bar{V}} = &z_2[-k\mu z_2 - \tilde{W}^T F(\vartheta) - \xi sign(z_2) - \varepsilon_l]\\ &+ \frac{1}{2}\tilde{W}^T\frac{\phi\phi^T}{m^2}\tilde{W} - \frac{3}{4}\mu_0\gamma_2^{-1}\tilde{W}^T\tilde{W}\\ &+ \tilde{W}^T\phi z_2 + \frac{\gamma_2}{4}W^T W\end{aligned} \tag{57}$$

Noting that $\phi = F(\vartheta)$,

$$\begin{aligned}\dot{\bar{V}} = &-k\mu z_2^2 - \xi sign(z_2)z_2\\ &- \varepsilon_l z_2 + \frac{\gamma_2}{4}W^T W\\ &- \tilde{W}^T\left[-\frac{1}{2}\frac{\phi\phi^T}{m^2} + \frac{3}{4}\mu_0\gamma_2^{-1}\right]\tilde{W}\end{aligned} \tag{58}$$

Let $\Delta = \sigma_{\max}(\gamma_2)\,\|W\|^2$, where $\sigma_{\max}(\cdot)$ denotes the maximum singular values. Taking the upper bound of (58) yields

$$\dot{V} \le -\left[\frac{3}{4}\mu_0\sigma_{\min}(\gamma_2^{-1}) - \frac{1}{2}\Phi_m\right]\left\|\tilde{W}\right\|^2 - k\mu z_{2m}^2 - \frac{z_2}{|z_2|}|z_2|\,\xi + z_{2m}\varepsilon_l + \Delta \tag{59}$$

Under the notion that the upper bound of z_2 is z_{2m}, then (59) can be deduced to

$$\bar{V} \le -\left[\frac{3}{4}\mu_0\sigma_{\min}(\gamma_2^{-1}) - \frac{1}{2}\Phi_m\right]\left\|\tilde{W}\right\|^2 - k\mu z_{2m}^2 - z_{2m}\left[\xi - \bar{\varepsilon}_l\right] + \Delta \tag{60}$$

where $\bar{\varepsilon}$ is the maximum bound of the approximation error ε_l. The error term z_2 and parameter estimation error $\tilde{W}$ will converge to a compact set around zero that is bounded by Δ with a condition that the design control parameter μ_0 be selected as follows:

$$\mu_0 > \frac{2}{3}\frac{\Phi_m/m_2^2}{\sigma_{\min}(\gamma_2^{-1})} \tag{61}$$

where $\sigma_{\min}(\cdot)$ denotes the minimum singular values and the control parameter ξ is selected such that $\xi > \bar{\varepsilon}_l$

This completes the proof. ■

Consequently:

- The boundedness of the closed-loop signal is ensured.
- The mean square tracking error is close to 0 by the tuning of parameters $\delta_s, \mu_0, m, \gamma_2, k, \mu, \xi$ and the NN architecture.

The designed control scheme is summarized below in six main steps as shown in the algorithm 1.

Block diagrams summarizing the control strategy are presented in Fig. (1) and Fig. (2) and describe in detail the proposed structure of the adaptive neural network controller. Fig. (1) and Fig. (2) show that the main concept behind the neural adaptive backstepping controller is to treat the CSTR plant as a nonlinear system. The neural network detailed in Fig. (2) shows the novelty of this work while implementing online learning through an adaptive law with the covariance resetting algorithm and allowing the adaptation process to be performed only if specified limits are not reached. As the parameters of the CSTR plant are assumed to vary with uncertainties, the adaptive backstepping block shown in Fig. (1) handles this delicate problem and ensures the robustness of the controller. The adaptive internal blocks are implemented in the controller structure to cover the inherent nonlinearity characterizing uncertain parameters according to the dynamics of the process.

Algorithm 1 NABC Algorithm

1. Initialization
   Initialize the simulation control parameters as shown in table 1.
2. Define the estimator of the uncertain parameter A_0 as given by equation (13).

$$\dot{\hat{\theta}}_1 = -\delta_s\hat{\theta}_1 + \gamma_1\left(1 - x_1 - \dot{y}_d\right)$$

3. Infer the equations of the quantities $\eta_1(\psi)$ and $\eta_2(x)$ as:

$$\begin{cases} \eta_1(\psi) = \dot{x}_1 e^{-1e4/x_2} + \dfrac{1e4\,x_1}{x_2^2}e^{-1e4/x_2} + \left(T_F - x_2 + A_1 x_1 e^{-1e4/x_2}\right) - k_1\dot{z}_1 \\ \qquad - \hat{\theta}_1\left(1 - x_1 - \dot{y}_d\right) + \hat{\theta}_1\left(\dot{x}_1 + \ddot{y}_d\right) \\ \eta_2(x) = \dfrac{1e\,4\,x_1}{x_2^2}e^{-1e\,4/x_2}\left(x_2 - T_{CF}\right) \end{cases}$$

4. Define the backstepping transformation as given by equation (7) and (15).

$$\begin{cases} \dot{z}_1 = 1 - \dot{y}_d - A_0\left(\alpha_1 + z_2\right) - x_1 \\ \dot{z}_2 = \eta_1(\psi) - A_3\eta_2(x)l(u) \end{cases}$$

5. Define the backstepping controller as:

$$u = \mu z_2 + \frac{1}{k}\xi\ sign\left(z_2\right) + u_{NN}$$

6. Synthesize the adaptive neural controller given by:

$$u_{NN} = \frac{1}{k}\hat{W}^T F(\vartheta)$$

7. Adaptive law with covariance resetting feature for Neural Network Weight Online Tuning.

$$\dot{\hat{W}} = \gamma_2\phi z_2 - \gamma_2^2\hat{W} \quad (36)$$
$$\dot{\gamma}_2 = \mu_0\gamma_2 - \gamma_2\phi\phi^T\gamma_2/m^2 \quad (37)$$

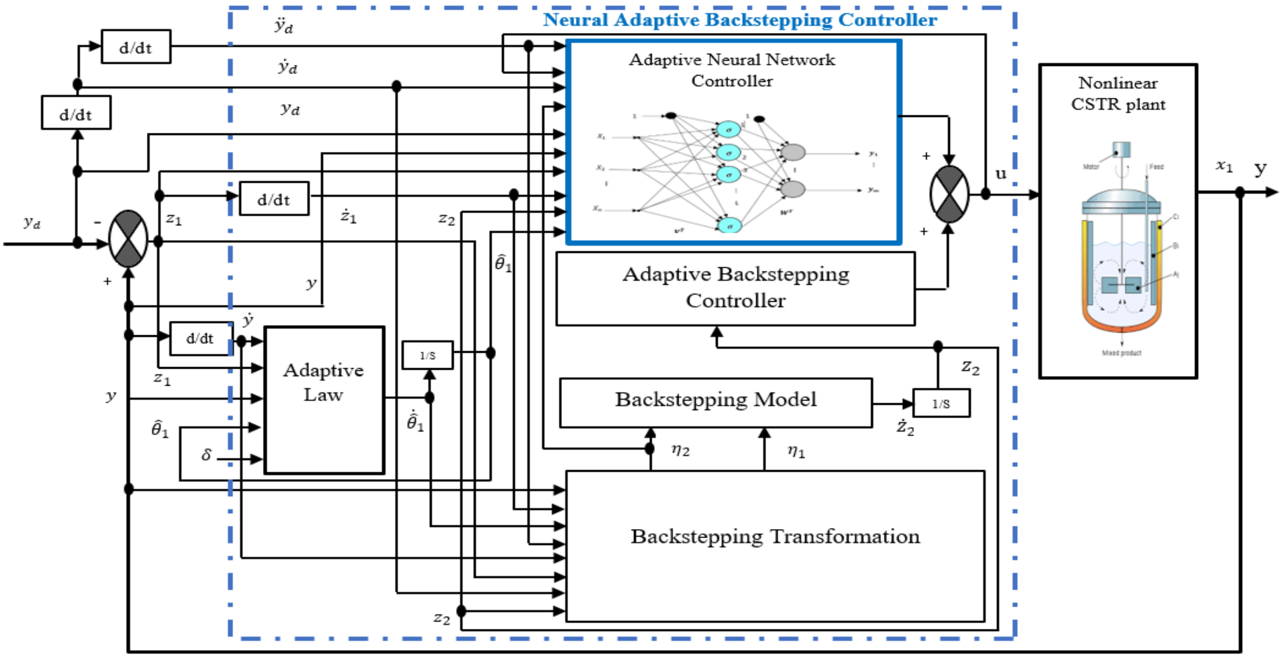

FIGURE 1. Block diagram of the closed-loop controlled plant.

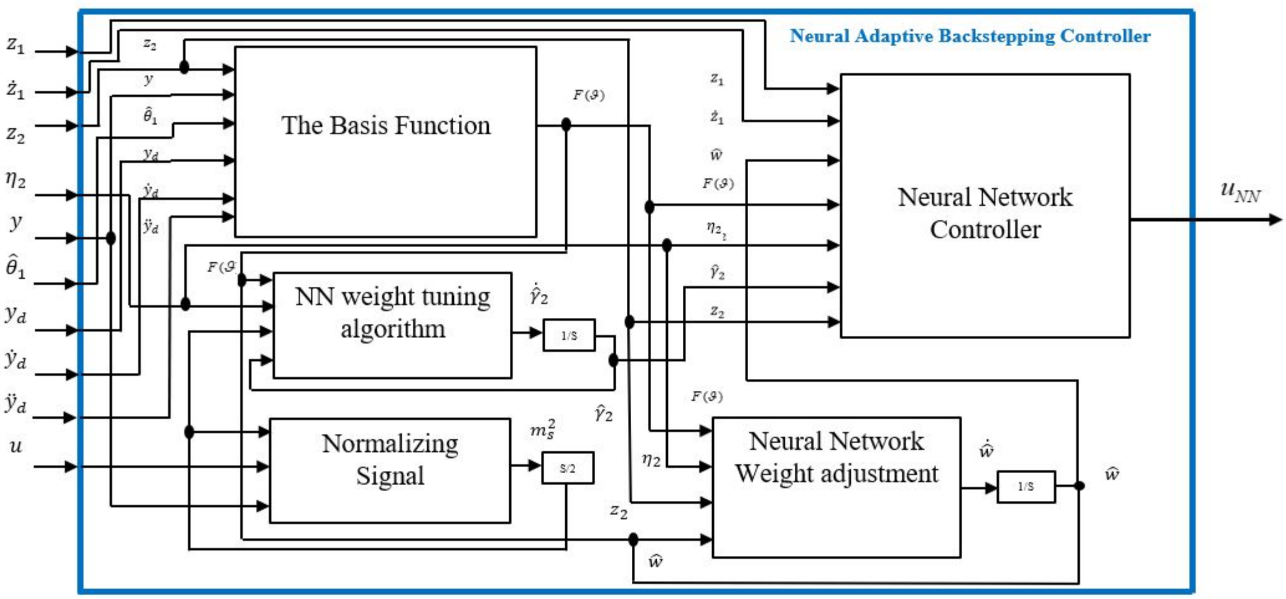

FIGURE 2. Block diagram of the NN adaptive control.

IV. MAIN RESULTS AND DISCUSSION

This section is dedicated to discussing and evaluating the approach developed in this work. A comparative study is conducted to evaluate the designed neural adaptive backstepping controller (NABC) scheme against a conventional proportional-integral-based controller and the adaptive controller (coined as adaptive uncertain controller (AUC)) developed in [47]. For the sake of brevity, one can easily exploit the block diagrams presented in Fig. (3) and Fig. (4), where a detailed analytical description is provided. The elaborated representation of the algorithm in block diagram gives an accurate block connection that is performed within the simulation study for easy reference.

The control object for the three fixed control techniques would be to enable the concentration state variable $y = c_A$ to track a reference input signal $r(t)$. To obtain a smooth reference input trajectory, a second-order reference linear system is exploited to form a continuous step change

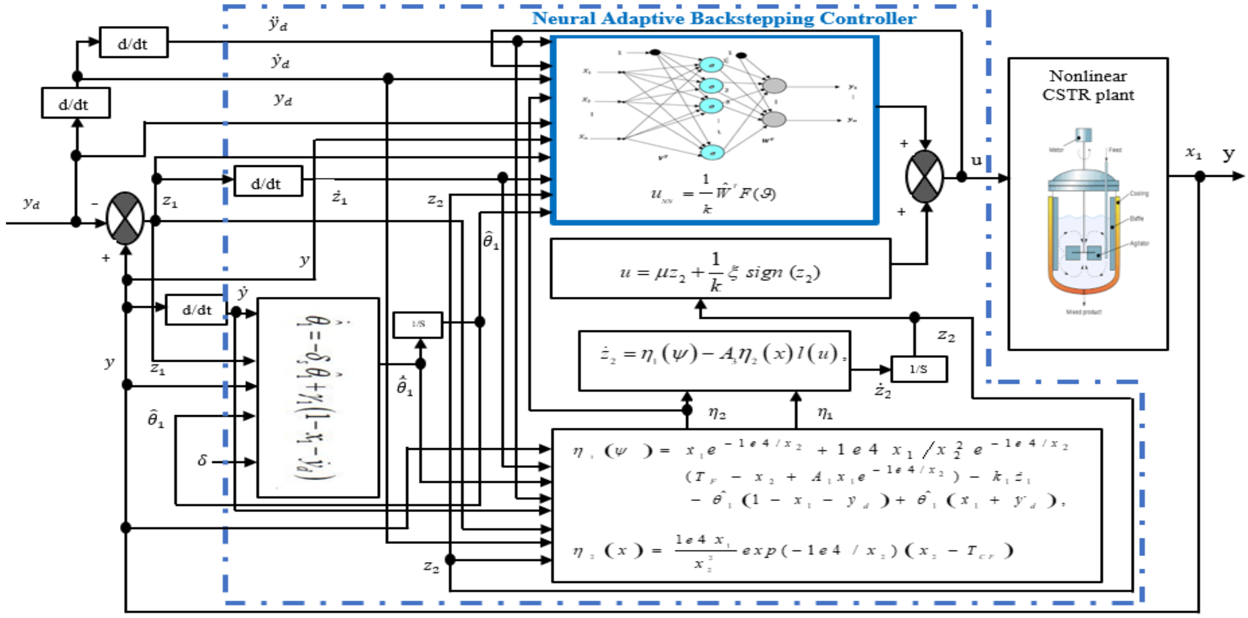

FIGURE 3. Analytical block diagram of the closed-loop controlled plant.

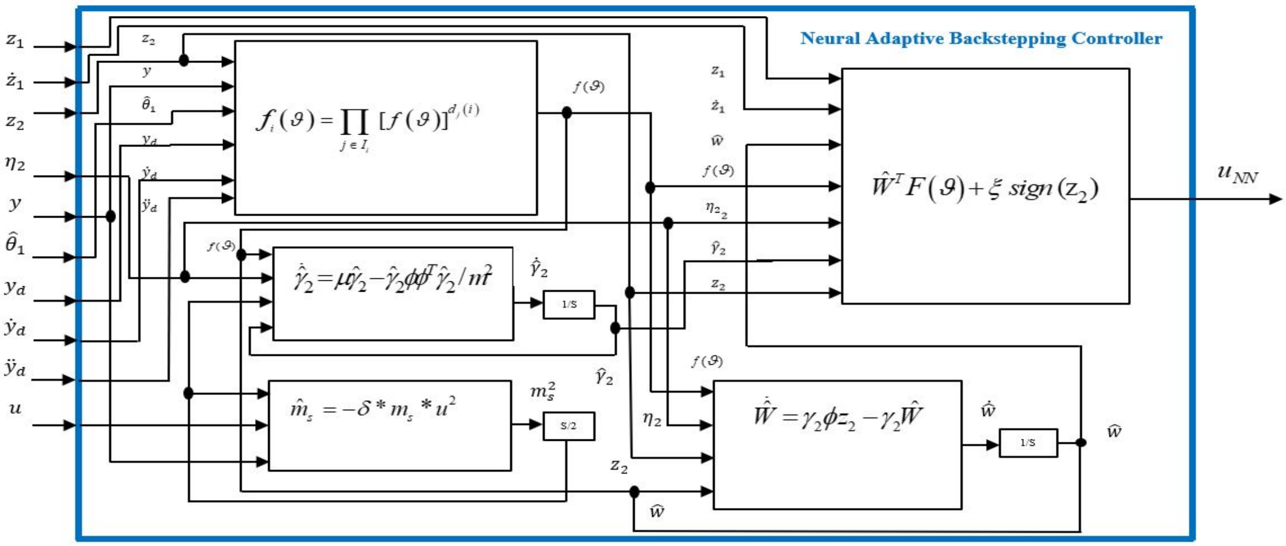

FIGURE 4. Analytical block diagram of the NN adaptive controller.

reference input characterizing the desired variable and its derivatives. From this perspective, a linear second-order model is shown as follows:

$$y_d(t) = (1 - \frac{\zeta\omega_n t}{\sqrt{1-\zeta^2}} \times \left((\sqrt{1-\zeta^2}) \cos(\omega_n dt) + \zeta \sin(\omega_n dt)) \right) r(t) \quad (62)$$

where $0 < \zeta < 1$ and $\omega_d = \omega_n\sqrt{1-\zeta^2}$ are used to set the step change reference input $r(t)$ to generate the desired output y_d and its first and second derivatives $\dot{y}_d$ and $\ddot{y}_d$, respectively. To assess the proposed NN scheme's control performance, an alternative PI control input frequently employed in chemical processes with control fixed gains k_c and T_i is defined as:

$$u_{pi} = k_c\varepsilon(s) + \frac{k_c}{T_i s}\varepsilon(s) \quad (63)$$

where $\varepsilon(s)$ is the tracking error. Note that gains k_c and T_i are chosen to provide a suitable response required for step variation $r(t)$ along the input reference of $\pm 0.02\ mol/l$ as well as a suitable concentration value of $0.1\ mol/l$. Note that the initial conditions of the CSTR state variables are fixed as follows: $c_{\min} = 0.08\ mol/l$ and $T_{A0} = 440\ K$ [48].

The numerical simulation conditions are set as shown in Table 3 [48].

TABLE 3. Simulation model parameters.

Parameter	Value
$C_{\min}$	$0.08\ mol\,/\,l$
T_{A0}	$440\ K$
Damping ratio ζ	0.9
Natural oscillation ω_n	$5\ rad$ / min
$y_d(0),\ \dot{y}_d(0),\ \ddot{y}_d(0)$	0.1, 0, 0
$k_c,\ T_i,\ u_{pi}(0)$	440, 0.8, 100 $l\,/\,min$
NN number of nodes	30
$w_m, \hat{w}(0), k_1, k, \gamma_1, \sigma$	30, 0, 1, 100, 1, 0.1

The simulation study outcomes are depicted in Figs. (5)-(8), where the different real output responses and their corresponding manipulated variables are drawn. Fig. (5) illustrates the perfect tracking behavior of the improved backstepping NN control avoiding any strong oscillations, as shown in Fig. (7) for both PI and AUC. The designed control input is presented in Fig. (6). The undesirable high-oscillation behavior is well mitigated in comparison with the results shown in Fig. (8) for the different manipulated variables. This performance can be explained by the interesting added value of the covariance resetting algorithm implementation in the least square estimation for the NN weight tuning algorithm, where the parameter settings are as follows:

$(m^2 = 1 + n_s^2, n_s^2 = m_s$ and $\dot{m}_s = -\delta m_s + u^2 + y^2)$. The implemented algorithm provides a valuable compensation for the neural network's lack of information regarding the CSTR plant dynamics. Indeed, to attenuate the oscillation in the AUC, the NN needed various learning periods (around five minutes) to reduce the tracking error. The average performance of the overall controllers can be appreciated by considering the quantitative summary results shown in Table 4, which reports the values of the control efforts, IAE, ISE

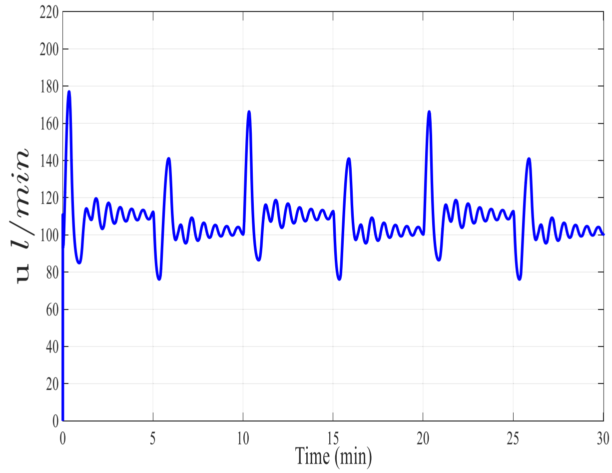

FIGURE 6. NN adaptive backstepping control input.

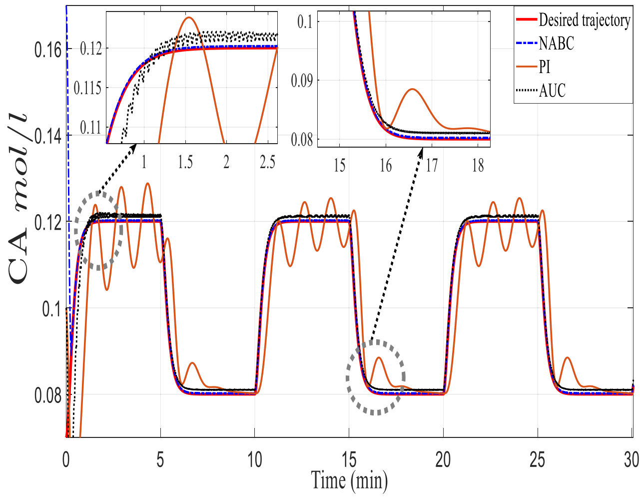

FIGURE 7. Output trajectory tracking of peer control strategies for a desired step change varying trajectory.

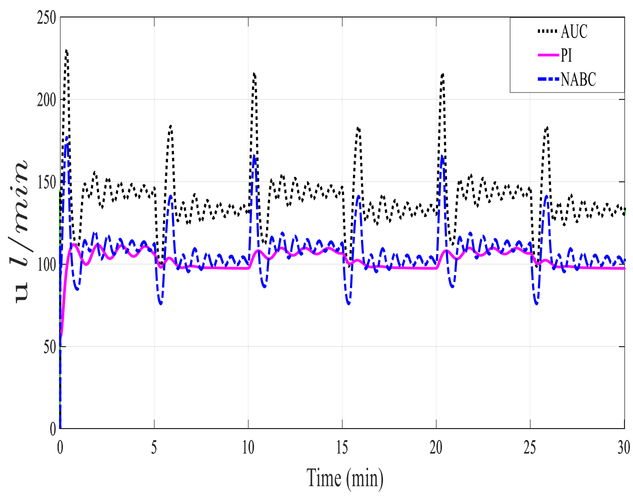

FIGURE 8. Control input signal of the NN adaptive backstepping controller against peer controllers.

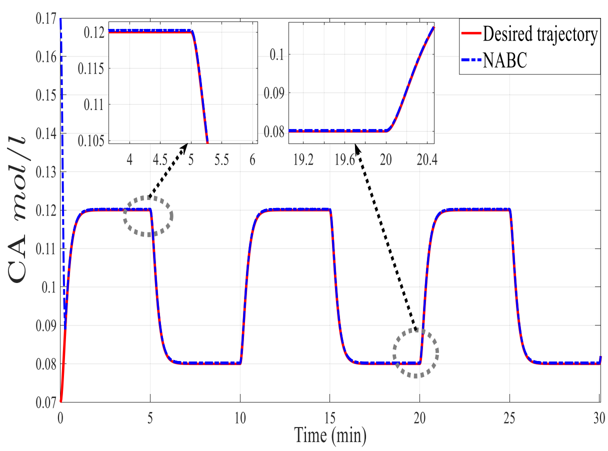

FIGURE 5. Output trajectory tracking using the NN adaptive backstepping controller.

TABLE 4. Results of a comparative performance study.

Control	Control Effort	IAE	ISE	Maximum Overshoot
NABC	1241	0.01	0.001	0.0
AUC [47]	3235	0.03	0.003	0.02
PI (63)	1108	0.15	0.006	0.08

and maximum overshoot where the output convergence is attained. Based on the values of the selected key performance indicators shown in Table 4, it can be concluded that besides guaranteeing global stabilization, the proposed NABC algorithm outperforms the rest in terms of minimal control effort and performance indices (IAE, ISE and overshoot). It is apparent to witness that the control effort is excessive for the case of the AUC. In contrast, this effort is comparable in magnitude for both PI-based control and improved backstepping NN control. However, the tracking error is substantially reduced in the case of the NABC, allowing the increased cost of the control effort to be tolerated with respect to PI-based control.

V. CONCLUSION

In this research work, a novel neural network adaptive controller had been presented pertaining to a non-affine nonlinear chemical process. A detailed step algorithm was given to perform the synthesized control scheme. The control structure and an adaptive learning approach were developed with the enhancement of an adaptive backstepping design and the Lyapunov stability method. It has been established that the proposed controller ensures stability as well as robust accurate trajectory tracking pertaining to the asymptotic closed-loop adaptive performance. A main enhancement was attained through the implementation of the covariance resetting algorithm in the least square estimation of the high-order NN weight tuning algorithm. The novel contribution is the online learning of the neural network through an adaptive law that includes a covariance resetting feature to allow the adaptation to run only if it does not reach a certain limit. This novelty prevented any possible occurrences of winding-up issues, which may lead to instability. In addition, the covariance resetting feature adaptation as a self-regulating mechanism promotes light computation, i.e., the learning occurs only when it is needed, and the adaptation can be automatically switched off when it is not necessary. In addition to excellent output trajectory tracking performance, the proposed approach has a profound benefit in terms of substantially lower control effort in comparison to the established work in the literature. In terms of applications in the petrochemical industry, lower control effort can translate to a more energy-efficient actuator, leading to lower costs over a long-run operation. The efficacy of the recommended control scheme has been depicted through a numerical simulation analysis. Future work will investigate the control problem of a CSTR model characterized by nonlinear dynamics with the existence of input saturation, time-varying parameters and non-measurable state variables.

REFERENCES

[1] T. Liu, Z. P. Jiang, and D. J. Hill, *Nonlinear Control of Dynamic Networks*. Boca Raton, FL, USA: Taylor & Francis, 2018.

[2] J. D. J. Rubio, "Robust feedback linearization for nonlinear processes control," *ISA Trans.*, vol. 74, pp. 155–164, Mar. 2018.

[3] O. Alshammari, M. N. Mahyuddin, and H. Jerbi, "An advanced PID type tracking control with fuzzy scheduled gains," *Int. J. Mech. Eng. Technol.*, vol. 9, no. 10, pp. 645–661, Oct. 2018.

[4] R. W. Koller and L. A. Ricardez-Sandoval, "A dynamic optimization framework for integration of design, control and scheduling of multi-product chemical processes under disturbance and uncertainty," *Comput. Chem. Eng.*, vol. 106, pp. 147–159, Nov. 2017.

[5] J. Young Choi and J. Farrell, "Adaptive observer backstepping control using neural networks," *IEEE Trans. Neural Netw.*, vol. 12, no. 5, pp. 1103–1112, 2001.

[6] D. X. Gao and H. Liu, "Optimal dynamic control for CSTR nonlinear system based on feedback linearization," in *Proc. IEEE Conf. Chin. Control Decis. (CCDC)*, May 2015, pp. 1298–1302.

[7] Z. Nassira, C. Mohamed, and N. Essounbouli, "Adaptive neural-network output feedback control design for uncertain CSTR system with input saturation," in *Proc. Int. Conf. Elect. Sci. Tech. Maghreb (CISTEM)*, Oct. 2018, pp. 1–6.

[8] L. Dong-Juan, "Adaptive neural network control for continuous stirred tank reactor process," *IFAC Proc. Volumes*, vol. 46, no. 20, pp. 171–175, Jan. 2013.

[9] C. Pozna and R. E. Precup, "An approach to the design of nonlinear state-space control systems," *Stud. Inform. Control*, vol. 27, no. 1, pp. 5–14, 2018.

[10] S. Ge, C. Hang, and T. Zhang, "Nonlinear adaptive control using neural networks and its application to CSTR systems," *J. Process Control*, vol. 9, no. 4, pp. 313–323, Aug. 1999.

[11] O. Alshammari, M. N. Mahyuddin, and H. Jerbi, "A survey on control techniques of a benchmarked continuous stirred tank reactor," *J. Eng. Sci. Technol.*, vol. 10, no. 13, pp. 3277–3296, Oct. 2018.

[12] C. Jia, X. Li, K. Wang, and D. Ding, "Adaptive control of nonlinear system using online error minimum neural networks," *ISA Trans.*, vol. 65, pp. 125–132, Nov. 2016.

[13] K. Uçak and G. Ö. Günel, "Model free adaptive support vector regressor controller for nonlinear systems," *Eng. Appl. Artif. Intell.*, vol. 81, pp. 47–67, May 2019.

[14] B. Mohamed, K. Kara, A. Oussama, and L. Hadjili, "Adaptive neural network PID controller," in *Proc. IEEE Conf. Ind. Commercial Power Syst. Eur. (EEEIC/I CPS Eur.)*, Jun. 2019, pp. 1–6.

[15] M. B. Triven and U. V. Ratnakumari, "Comparative study of neoteric adaptive model predictive controller with model predictive control for temperature regulation of CSTR," in *Proc. IEEE Conf. Commun. Power Embedded Syst. (SCOPES)*, Oct. 2016, pp. 2024–2120.

[16] Y. Fan, X. Huang, H. Shen, and J. Cao, "Switching event-triggered control for global stabilization of delayed memristive neural networks: An exponential attenuation scheme," *Neural Netw.*, vol. 117, pp. 216–224, Sep. 2019.

[17] Y. Fan, X. Huang, Y. Li, J. Xia, and G. Chen, "Aperiodically intermittent control for quasi-synchronization of delayed memristive neural networks: An interval matrix and matrix measure combined method," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 49, no. 11, pp. 2254–2265, Nov. 2019.

[18] M. Chen, S. Sam Ge, and B. How, "Robust adaptive neural network control for a class of uncertain MIMO nonlinear systems with input nonlinearities," *IEEE Trans. Neural Netw.*, vol. 21, no. 5, pp. 796–812, May 2010.

[19] M. Shyamalagowri and R. Rajeswari, "Neural network predictive controller based nonlinearity identification case study: Nonlinear process reactor–CSTR," *Adv. Mater. Res.*, vols. 984–985, pp. 1326–1334, Jul. 2014.

[20] K. A. Kosanovich, M. J. Piovoso, V. Rokhlenko, and A. Guez, "Nonlinear adaptive control with parameter estimation of a CSTR," *J. Process Control*, vol. 5, no. 3, pp. 137–148, Jun. 1995.

[21] K. Lu, Z. Liu, G. Lai, C. L. P. Chen, and Y. Zhang, "Adaptive consensus tracking control of uncertain nonlinear multiagent systems with predefined accuracy," *IEEE Trans. Cybern.*, to be published.

[22] Y.-J. Liu, S. Li, S. Tong, and C. L. P. Chen, "Adaptive reinforcement learning control based on neural approximation for nonlinear discrete-time systems with unknown nonaffine dead-zone input," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 30, no. 1, pp. 295–305, Jan. 2019.

[23] X. Yu, M. O. Efe, and O. Kaynak, "A backpropagation learning framework for feedforward neural networks," *IEEE Int. Symp. Circuits Syst.*, vol. 3, pp. 700–702, May 2001.
[24] J. Na and G. Herrmann, "Online adaptive approximate optimal tracking control with simplified dual approximation structure for continuous-time unknown nonlinear systems," *IEEE/CAA J. Autom. Sinica*, vol. 1, no. 4, pp. 412–422, Oct. 2014.
[25] M. Charfeddine, K. Jouili, and H. Jerbi, "Linearizing control with a robust relative degree based on a Lyapunov function: Case of the ball and beam system," *Int. Rev. Mode. Simulations*, vol. 3, no. 2, pp. 219–226, Apr. 2010.
[26] H. Jerbi and E. B. Braiek, "On the design of linearizing controller for nonlinear discrete systems," in *Proc. IEEE Int. Conf. Syst. Man, Cybern.*, vol. 1, Oct. 1999, pp. 33–37.
[27] J. Nayak, B. Naik, and H. Behera, "A novel nature inspired firefly algorithm with higher order neural network: Performance analysis," *Eng. Sci. Technol., Int. J.*, vol. 19, no. 1, pp. 197–211, Mar. 2016.
[28] L. Wang, Y. Zeng, and T. Chen, "Back propagation neural network with adaptive differential evolution algorithm for time series forecasting," *Expert Syst. Appl.*, vol. 42, no. 2, pp. 855–863, Feb. 2015.
[29] H. Pang, X. Zhang, J. Yang, and Y. Shang, "Adaptive backstepping-based control design for uncertain nonlinear active suspension system with input delay," *Int. J. Robust. Nonlinear Control*, vol. 29, no. 16, pp. 5781–5800, Nov. 2019.
[30] M. Charfeddine, K. Jouili, and H. Jerbi, "Output tracking control design for non-minimum phase systems: Application to the ball and beam model," *Int. Rev. Autom. Control*, vol. 4, no. 1, pp. 47–55, Jan. 2011.
[31] N. BenHadj and H. Jerbi, "A polynomial approach of linearizing control synthesis for nonlinear analytic systems," *J. Syst. Analy. Model. Simul.*, vol. 38, pp. 19–28, Jan. 2000.
[32] J. Xu, X. Wang, and L. Zhang, "Approximation-based robust adaptive backstepping prescribed performance control for a huger class of nonlinear systems," *Math. Problems Eng.*, vol. 2019, pp. 1–13, Aug. 2019.
[33] I. Kanellakopoulos, P. Kokotovic, and A. Morse, "Systematic design of adaptive controllers for feedback linearizable systems," *IEEE Trans. Autom. Control*, vol. 36, no. 11, pp. 1241–1253, Nov. 1991.
[34] S. John and J. O. Pedro, "Neural network-based adaptive feedback linearization control of antilock braking system," *Int. J. Artif. Intell.*, vol. 10, no. S13, pp. 21–40, 2013.
[35] S.-T. Zhao and X.-W. Gao, "Robust adaptive control for a class of uncertain non-affine nonlinear systems using neural state feedback compensation," *J. Central South Univ.*, vol. 23, no. 3, pp. 636–643, Mar. 2016.
[36] O. Alshammari, M. N. Mahyuddin, and H. Jerbi, "An advanced PID based control technique with adaptive parameter scheduling for a nonlinear CSTR plant," *IEEE Access*, vol. 7, pp. 158085–158094, 2019.
[37] K. Miroslav, L. Kanellakopoulos, and V. Peter, *Nonlinear and Adaptive Control Design*. New York, NY, USA: Wiley, 1995.
[38] T. Zhang, "Adaptive neural network control for strict-feedback nonlinear systems using backstepping design," *Automatica*, vol. 36, no. 12, pp. 1835–1846, Dec. 2000.
[39] P. A. Loannou and J. Sun, *Robust Adaptive Control*. New York, NY, USA: Dover, 2012.
[40] L.-B. Wu, X.-Q. He, and D.-Q. Zhang, "Cooperative adaptive fuzzy control for a class of uncertain non-linear multi-agent systems with time delays," *J. Control Decision*, vol. 4, no. 3, pp. 131–152, Jul. 2017.
[41] H. K. Khalil, *Nonlinear Systems*. Upper Saddle River, NJ, USA: Prentice-Hall, 2002.
[42] A. Safaei and M. N. Mahyuddin, "Adaptive model-free control based on an ultra-local model with model-free parameter estimations for a generic SISO system," *IEEE Access*, vol. 6, pp. 4266–4275, 2018.
[43] M. N. Mahyuddin, C. Z. Wei, and M. R. Arshad, "Neuro-fuzzy algorithm implemented in Altera's FPGA for mobile robot's obstacle avoidance mission," in *Proc. TENCON IEEE Region 10 Conf.*, Singapore, Nov. 2009, pp. 1–6.
[44] M. N. Mahyuddin, G. Herrmann, J. Na, and F. L. Lewis, "Finite-time adaptive distributed control for double integrator leader-agent synchronisation," in *Proc. IEEE Int. Symp. Intell. Control*, Dubrovnik, Croatia, Oct. 2012, pp. 714–720.
[45] A. Safaei and M. N. Mahyuddin, "Optimal model-free control for a generic MIMO nonlinear system with application to autonomous mobile robots," *Int. J. Adapt. Control Signal Process.*, vol. 32, no. 6, pp. 792–815, Jun. 2018.
[46] Q.-Y. Xu and X.-D. Li, "HONN-based adaptive ILC for pure-feedback nonaffine discrete-time systems with unknown control directions," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 31, no. 1, pp. 212–224, Jan. 2020.
[47] T. Zhang and M. Guay, "Adaptive control of uncertain continuously stirred tank reactors with unknown actuator nonlinearities," *ISA Trans.*, vol. 44, no. 1, pp. 55–68, Jan. 2005.
[48] G. Lightbody and G. Irwin, "Direct neural model reference adaptive control," *IEE Proc.-Control Theory Appl.*, vol. 142, no. 1, pp. 31–43, Jan. 1995.

OBAID ALSHAMMARI received the B.Sc. and M.Sc. degrees in electrical engineering from Pittsburg State University, Pittsburg, PA, USA, in 2008 and 2012, respectively. He is currently pursuing the Ph.D. degree with the School of Electrical and Electronic Engineering, Universiti Sains Malaysia, Pulau Pinang, Malaysia. He received a scholarship from the Saudi Arabian Government.

MUHAMMAD NASIRUDDIN MAHYUDDIN received the B.Eng. degree (Hons.) in mechatronic engineering from the International Islamic University of Malaysia, in 2004, the M.Eng. degree (Hons.) in mechatronics and automatic control from the Universiti Teknologi Malaysia, in 2006, and the Ph.D. degree in mechanical engineering from the University of Bristol, in 2014, specializing in control and robotics. Soon after graduation, he started his industrial career as an Application Engineer at Agilent Technologies, in 2004, working with Motion Control products. He was appointed as a Senior Associate Teacher by the University of Bristol via contract, giving lectures in nonlinear control with application to robotics, from October 2011 to July 2012, and was involved in a research project funded by Jaguar Land Rover. He was invited as a Visiting Professor at MIS Lab, Universite de Picardie Jules Verne, France, in March and April 2018. He was also affiliated with Continental Automotive Components during his Sabbatical in 2019, working on a closed-loop vehicle instrument cluster test. He is currently an Associate Professor with the School of Electrical and Electronics Engineering, Universiti Sains Malaysia, and is also an Honorary Visiting Fellow at the Faculty of Engineering, University of Bristol. His current research interests include distributed adaptive control, cooperative control, as well as nonlinear control and parameter estimation involving mechatronics system and robotics. He received a Secondment International Grant (S0419_01) for September 2019, February 2020, and March 2020 research visit from R.A.I.N. Programme (Robotics and A.I. research) hosted by The University of Manchester, U.K.

HOUSSEM JERBI was born in Tunisia, in 1971. He received the Ph.D. degree in electrical engineering from the ENIT University of Al Manar, Tunis, Tunisia, in 2000. He is currently an Associate Professor with the Department of Industrial Engineering, College of Engineering, University of Hail, Saudi Arabia, and has been the main consultant of the GDPMO—UOH, since 2014. From 2000 to 2010, he was an Assistant Professor with the College of Science, Sfax Tunisia. Since 2010, he has been a Faculty Member of the University of Hail. He has published more than 100 scientific papers and book chapters in the field of nonlinear control and systems. His research interests include stability analysis, advanced control, big data control system engineering, and fault-tolerant control.