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An Advanced PID Based Control Technique With Adaptive Parameter Scheduling for A Nonlinear CSTR Plant

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ABSTRACT The continuous stirred tank reactor (CSTR) tends to reveal unstable severe nonlinear behavior when the operating level changes. As investigated in an earlier work, the hard nonlinearity nature of the CSTR originates from multiple probable sets of states for the same reaction in the same CSTR under identical ongoing inlet conditions. The previous work concluded, and this paper will discuss, that nonlinear processes with dynamic trajectories will involve a degrading control performance whenever the measured process variable evolves away from the designed level of the desired output trajectory. In this work, this problem will be examined for temperature tracking control on a CSTR with an adaptive fuzzy gain-scheduling proportional-integral-derivative (AFGS-PID) controller scheduled for a dynamic output trajectory. It will be proven that the AFGS-PID has better tracking performance than the fuzzy gain scheduling (FGS-PID) and conventional PID. Although all three controllers demonstrate the same level of control efforts, AFGS-PID has the smallest IAE and ISE. The lowest settling time being exhibited by AFGS-PID also proves that the intended regulator can rapidly track the desired coolant jacket temperature. A Lyapunov analysis is presented to prove the stability of the closed-loop and support the simulated result in the comparative study.

INDEX TERMS Adaptive control, CSTR, nonlinear system, fuzzy logics, stability analysis, feedback linearization.

I. INTRODUCTION

The literature shows that the adaptive control design has been used in industrial cases in which there is a little theoretical information regarding the process dynamics. It has also been employed to compensate the inherent continuous variations in plant parameters because of element and process module faults and operational set point deviations. The universal design for the complex plant adaptive control, which is characterized by time variations, is to consider their impacts as unbounded and random disturbances so that the problem is converted into one of robustness [1]. This technique has been applied to LTV, where the variables and parameters slightly and gradually change, or in a discontinuous form, but the discontinuity occurs across large time gaps [2]–[4]. In [5], an adaptive design for a class of nonlinear systems has been examined in the precise feedback linearization approach with indefinite parameter perturbations, and the backstepping control design has been implemented. A related study employing a similar approach in a strict-feedback system setup was proposed in [6]. Other works that use a robustification technique, *i.e.*, a projection adaptive law in a state-feedback control system, can be found in [7]. Apart from handling the nonlinear complex system in its entirety, another control approach is to use the inner time-varying theory of nonlinear systems (for example, the group of systems comprising nonlinear state dynamic interpolation in the strict feedback form) and create backstepping control guidelines that are adapted to every dynamic component of the nonlinear models [8]. In the case of an adaptive design issue of nonlinear time-varying systems, only a class of systems in the precise feedback mode is considered, and only a few outcomes persist [9].

In this paper, a more general class of nonlinear affine systems is studied. An adaptive control methodology is introduced in the scheme of the fuzzy logic-based gain scheduling controller. As a particular case study, the synthesis is built around the nonlinear CSTR model with multiple

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varying operating conditions and nonlinearities. The concept of employing structural approximative function structures with standard representative approximation characteristics, such as fuzzy systems, to handle random continuous nonlinearities has been extensively exploited in the adaptive design for nonlinear processes [10]. In fact, online stable-adaptive approximation-based fuzzy techniques have been considerably affected by the works that use fuzzy sets as the estimators of nonlinear functions [11] as well as the work employing fuzzy schemes for the identical objective [12], and dynamic neural networks [13]. The fuzzy and neural techniques are mostly equivalent; they mainly differ in the selected estimator structure. In reality, to bridge the divide between fuzzy and neural techniques, many experts (e.g., [14], [15]) introduce adaptive methods using a group of parameterized functions that comprise both fuzzy systems and neural networks.

Linear parameter approximators are presented in [14], [16], [17], [18], and nonlinear parameter approximators are presented in [13], [19], [20]. Last, the majority of studies [20], [21] develop indirect adaptive management to recognize the system dynamics and further produce a control input according to the principle of certainty equivalence. However, only a few works (e.g., [14], [22]) use the direct technique, which directly produces a control strategy to ensure steadiness, as it is not always straightforward to create the control input scheme without awareness regarding the dynamics of the system.

In [23], a similar motivation with the use of an adaptive neural-network (NN) algorithm has been adopted in the nonlinear feedback linearization for the tracking control of a nonlinear system (a Furuta pendulum). A two-layer perceptron was used in this particular neural network scheme. The first principle dynamic model of the plant must be transformed into a normal form prior to the design and synthesis of the nonlinear adaptive NN control. On contrary, the complexity of the showcased method depends on the critical choice of the number of neuron nodes to incorporate in the adaptive NN algorithm. Others escape the dilemma in deciding the size of the neural network or the fuzzy membership function definition by resorting to a model-free approach, as in [24]. It was also rigorously proven in [23] that the dynamic of the tracking error (examining the resulting internal dynamics) converges to a uniformly ultimately bounded (UUB) region.

In this study, an adaptive fuzzy gain-scheduling proportional-integral-derivative controller, or AFGS-PID controller approach, is proposed as a benchmark nonlinear model of a CSTR, which depends on the exogenous scheduling trajectory. This process comprises nonlinear dynamics with several stable and unstable equilibrium points and may resort to detect unstable nonlinear behavior when the nonmonotonic operating trajectory changes [25]–[27]. This problem also addresses a time-varying nonlinear condition that can be a generalized in nonlinear adaptive control theory [14], [22]. To simplify the advanced stable PID adaptive scheduled gain control [14], following the universal technique in [8] and [9], the adaptive guidelines here are localized so that only the portion of the estimator parameters that represent the ‘‘scheduled area’’ is updated each time. Moreover, apart from other designed control, in this study, the proposed AFGS-PID controller is devised and assessed, which can display better temporary behavior since it appears to quickly learn and adapt. Without loss of generality, the proposed method can be exploited for the class of nonlinear input affine systems with reduced relative degree value and where the internal unobservable dynamics can be compensated with stable bounded variables.

To manage the nonlinear control issue by examining the localized, simplified plant approximations, the control approach examined here uses some general opinions of the gain scheduling formalism, which manages linearized nonlinear models along the operating points or reference trajectories [28], [29]. The gain scheduled regulator is extensively utilized for industrialized use, but only local steadiness outcomes have been found to date because of the difficulty in the analysis of stability [12], [30].

Other related findings are found in the literature of the parallel distributed compensation [31], [32], where experts suppose the presence of a model of linearized system dynamics interpolation. A linear control design is devised in these areas and further explored by using the same system structure interpolation. Nevertheless, instead of interpolating controllable linear systems, through [8] (but not limited to the precise feedback form), the study is concentrated on utilizing fuzzy PID feedback controllers as the ‘‘parts’’ to form the ‘‘universal’’ nonlinear system through interpolation [33].

Moreover, the CSTR model examined in this work is sufficiently significant so that it can be more practically used. The synthesis will be illustrated through the objective of a temperature output trajectory tracking, where the advanced adaptive designed scheme can perform with typical efficiency.

This paper is organized as follows. The localized framework model of the CSTR model is presented in Section II. In Section III, the synthesized control structure will be exposed, and the global control design will be provided. The adaptive techniques and assessment of system stability are evaluated through a simulation study in Section IV. Section V depicts other equivalent control approaches to compare with the designed adaptive control in this paper by using the CSTR model to demonstrate the achievements of the recommended adaptive fuzzy PID control technique. Concluding remarks are provided in the last section.

II. PROCESS MODELLING ANALYSIS

The following differential equation represents the nonlinear third-order dynamic model of a CSTR plant:

$$\begin{cases} \dfrac{dC_A}{dt} = \dfrac{Q_r}{V_r}\left(C_{Af}-C_A\right)-k_0 e^{\left(-\frac{E_a}{RT}\right)} C_A \\ \dfrac{dT}{dt} = \dfrac{Q_r}{V_r}\left(T_f-T\right)-\dfrac{\Delta H}{\rho C_p} k_0 e^{\left(-\frac{E_a}{RT}\right)} C_A + \dfrac{U_A}{\rho C_p V_r}\left(T_j-T\right) \\ \dfrac{dT_j}{dt} = \dfrac{U_A}{\rho C_p V_r}\left(T-T_j\right)+\dfrac{Q_c}{V_j}\left(T_{jf}-T_j\right) \end{cases} \tag{1}$$

where C_A is the concentration of the product inside the CSTR; T is the reaction temperature of the CSTR product; T_j is the coolant temperature feeding into the enveloping jacket; and Q_c is the coolant flow rate. In this paper, the control input design is synthesized while considering the reaction temperature as the system output. This latter choice is justified based on two reasons. First, reliable and consistent concentration measurements are typically unavailable in industrial environments. Moreover, the scheme in this work requires the estimation of the time derivative of C_A, which is difficult to perform in practice. Second, there is a restriction on the maximum acceptable temperature to avoid secondary reactions in the reactor. The reaction temperature is consequently considered more critical in industrial environments and, thus, attracts more research development interest.

The formulation in (1) utilizes the above state variables with the defined manipulated variable of the CSTR, for which the parameters are organized in Table 1.

TABLE 1. CSTR Model Parameters with Their Corresponding Significances and Values.

	Parameters	Values
Volumetric flowrate	Qr	$0.2 m^3 / min$
Volume	Vr	$2 m^3$
Constant	k_0	$3.5 10^6 min^{-1}$
Activation energy	Ea	$49.884 \, kJ/mol$
Molar gas constant	R	$8.33 10^{-3} \, kJ/mol.°C$
Enthalpy of reaction	$-\Delta H$	$500 \, kJ/mol$
Concentration of the feed	C_{Af}	$100 mol / m^3$
Feed temperature	T_f	$30°C$
Specific heat capacity at constant pressure	Cp	$4.2 \, kJ/kg.°C$
Density of the reactant	ρ	$100 kg / m^3$
Thermal transfer coefficient	U_A	$252 kj / \min.°C$
Volume of the envelope	V_j	$3.84 m^3$

An equivalent state-space representation can be derived from (1) to yield the following form,

$$\begin{cases} \dot{x} = F(x) + G(x)u \\ y = h(x) \end{cases} \tag{2}$$

where $x = [C_A \; T \; T_j]^T = [x_1 \; x_2 \; x_3]^T \in \mathbb{R}^3$; $u = Q_c$; and $y = h(x) = x_2$ is the output variable,

$$F(x) = \begin{bmatrix} \frac{Q_r}{V_r}(C_{Af} - x_1) - k_0 e^{\left(-\frac{E_a}{Rx_2}\right)} x_1 \\ \frac{Q_r}{V_r}(T_f - x_2) - \frac{\Delta H}{\rho C_p} k_0 e^{\left(-\frac{E_a}{Rx_2}\right)} x_1 + \frac{U_A}{\rho C_p V_r}(x_3 - x_2) \\ \frac{U_A}{\rho C_p V_r}(x_2 - x_3) \end{bmatrix}$$

and

$$G(x) = \begin{bmatrix} 0 \\ 0 \\ \frac{u}{V_j}(T_{if} - x_3) \end{bmatrix}$$

In this paper, we seek to control the temperature of the reactant by manipulating the coolant flow rate. To facilitate the control design and synthesis, (1) must be transformed into a normal form as in [34].

As presented in [35], to find an inbound input-output relationship, one must derive output y, and the number of times to derive the output corresponds to the system "relative degree".

When deriving the output, we obtain:

$$\begin{cases} \dot{y} = L_f h(x) + (L_G h(x))u \\ \ddot{y} = L_f^2 h(x) + (L_G L_f h(x))u \end{cases} \tag{3}$$

with

$$\begin{cases} L_f h(x) = \frac{Q_r}{V_r}(T_f - x_2) - \frac{\Delta H}{\rho C_p} k_0 e^{\left(-\frac{E_a}{Rx_2}\right)} x_1 \\ \qquad + \frac{U_A}{\rho C_p V_r}(x_3 - x_2) \\ L_f^2 h(x) = \begin{bmatrix} \frac{\partial \dot{x}_2}{x_1} & \frac{\partial \dot{x}_2}{x_2} & \frac{\partial \dot{x}_2}{x_3} \end{bmatrix} \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} \end{cases}$$

and

$$\begin{cases} L_G h(x) = 0 \\ L_G L_f h(x) = \frac{U_A (T_{if} - x_3)}{V_j \rho C_p V_r} \end{cases}$$

The control input appears for the second derivative of the output; consequently, the relative degree of the third-order CSTR model is 2, which is less than the system order. Thus, the dynamics of the studied CSTR are decomposed into an external input-output part and an unobservable internal part. Let us consider the nonlinear coordinate transformation given by:

$$\varnothing(x) = \begin{bmatrix} x_2 \\ \frac{Q_r}{V_r}(T_f - x_2) - \frac{\Delta H}{\rho C_p} k_0 e^{\left(-\frac{E_a}{Rx_2}\right)} x_1 + \frac{U_A}{\rho C_p V_r}(x_3 - x_2) \\ q_1(x) \end{bmatrix} \tag{4}$$

where $q_1(x)$ is a dynamic compensator, which is obtained by solving the following equation:

$$L_G q_1(x) = \begin{bmatrix} \frac{\partial(q_1(x))}{\partial x_1} & \frac{\partial(q_1(x))}{\partial x_2} & \frac{\partial(q_1(x))}{\partial x_3} \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ \frac{T_{jf} - x_3}{V_j} \end{bmatrix} = 0 \tag{5}$$

One of the solutions for this equation can be written as:

$$q_1(x) = x_1$$

It is possible to obtain the normal form using the change of coordinates $\varnothing(x)$:

$$\begin{bmatrix} \zeta_1 \\ \zeta_2 \\ \gamma \end{bmatrix} = \varnothing(x) = \begin{bmatrix} x_2 \\ \dot{x}_2 \\ q_{1(x)} \end{bmatrix} \tag{6}$$

The normal form using the change of coordinates is defined by:

$$\begin{cases} \dot{\zeta}_1 = \zeta_2 \\ \dot{\zeta}_2 = \alpha(\zeta,\gamma) + \beta(\zeta,\gamma)u \\ \dot{\gamma} = q_1(\zeta,\gamma) \\ y = x_2 \end{cases} \tag{7}$$

and

$$\alpha(\zeta,\gamma) = L_F^2 h(x)$$

$$\beta(\zeta,\gamma) = L_G L_F h(x) = \frac{U_A\left(T_{if} - x_3\right)}{V_j \rho C_p V_r}$$

Remark: The internal dynamics $\dot{\gamma}$ can be shown to be bounded later in the illustrative example because $q_1 = x_1$; the corresponding product concentration will eventually settle at a definite steady-state value.

III. ADAPTIVE FUZZY-BASED GAIN SCHEDULING CONTROL DESIGN

We present the transformed system (7) in a compact form,

$$\dot{\chi} = A_0\chi + b\tau, \tag{8}$$

where $\chi = \left[\zeta_1\ \zeta_2\right]^T$; consequently, $\dot{\chi} = \left[\dot{\zeta}_1\ \dot{\zeta}_2\right]^T$; $b = \left[0\ 1\right]^T$ is the input matrix; $A_0 = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$ and $\tau = \Xi(\chi) + \beta(\chi)u$. Ξ is the nonlinearity. Let $e = y_d - y$ and $\dot{e} = \dot{y}_d - \dot{y}$; $\varepsilon = \left[e\ \dot{e}\right]^T \in \mathbb{R}^2$ such that

$$\dot{\varepsilon} = A_0\varepsilon + b[\Xi(\chi) + \beta(\chi)u + \ddot{y}_d] \tag{9}$$

To establish a closed-loop system matrix that is Hurwitz, we add and subtract $b\eta$,

$$\dot{\varepsilon} = A_0\varepsilon - b\eta + b[\eta + \Xi(\chi) + \beta(\chi)u + \ddot{y}_d] \tag{10}$$

where η is defined as

$$\eta = D_p e + \sigma D_d \dot{e} = \overline{D}^T\varepsilon, \tag{11}$$

where $\sigma > 0$, D_p and D_d are the selected controller gains such that $A_{cl} = A_0 - b\bar{D}$ is Hurwitz. Eq. (10) yields

$$\dot{\varepsilon} = A_{cl}\varepsilon + b[\bar{D}\varepsilon + \Xi(\chi) + \beta(\chi)u + \ddot{y}_d] \tag{12}$$

The control signal u (to be designed) can be decomposed to

$$u = \frac{1}{\beta(\chi)}\left[u_{servo} + u_{fz} - \rho\kappa\right] \tag{13}$$

where u_{servo} is the control signal to design to track the desired trajectory, u_{fz} is the compensation signal executed by the fuzzy logic controller, and κ is the robustification signal with design constant $\rho = \left[\rho_1\ \rho_2\right]^T \in \mathbb{R}^2$. $\beta(\chi)$ is invertible knowing that the system is feedback-linearizable as described in [33] and [35].

There is a solution for a symmetric positive definite matrix P such that

$$A_{cl}^T P + PA_{cl} = -Q \tag{14}$$

where Q is a positive definite matrix.

Assumption 1: signals y_d, $\dot{y}_d$ and $\ddot{y}_d$ are bounded and continuous.

Substitute the control signal u from (14) into (13),

$$\dot{\varepsilon} = A_{cl}\varepsilon + b[\bar{D}\varepsilon + \Xi(\chi) + u_{servo} + u_{fz} - \rho\kappa + \ddot{y}_d] \tag{15}$$

Let $u_{servo} = -\bar{D}\varepsilon - \ddot{y}_d$ such that,

$$\dot{\varepsilon} = A_{cl}\varepsilon + b[\Xi(\chi) + u_{fz} - \rho\kappa] \tag{16}$$

A. FUZZY LOGIC COMPENSATION DESIGN

According to [36]–[38], the fuzzy logic control system of the zero-order Mamdani fuzzy system performs mapping from input vector $\vec{\tilde{x}} = \left[\tilde{x}_1, \cdots, \tilde{x}_m\right]^T \in \Omega_x \subset \mathbb{R}^m$ to a scalar output variable $\Gamma_F \in \mathbb{R}$, where $\Omega_{x1} \times \cdots \times \Omega_{xm}$ and $\Omega_{xi} \subset \mathbb{R}$. based on the singleton fuzzifier, product inference engine, center average defuzzifier and fuzzy rule base, which can be represented by a set of IF-THEN rules, R^k : If $\tilde{x}_1$ is G^k and ... and $\tilde{x}_m$ is G_m^k, then Γ_F is the crisp output of the k^{th} rule is $\Gamma_F^k (k = 1, \ldots, N)$, where $G^k \in \left[F_i^1, \ldots, F_r^m\right]$.

The ultimate fuzzy block outcomes can be represented by:

$$u_{fz}(\tilde{x}_i) = \frac{\sum_{l=1}^{N} \Gamma^l \left(\prod_{i=1}^{m} \mu_F(\tilde{x}_i)\right)}{\sum_{l=1}^{N} \left(\prod_{i=1}^{m} \mu_F(\tilde{x}_i)\right)} \tag{17}$$

where Γ^l is the crisp output of the lth rule; $\mu_F(\tilde{x}_i)$ is the membership function value of the fuzzy variable. The output of the fuzzy system is equivalently represented by the linear-in-parameter model (LIP),

$$u_{fz}(\tilde{x}_i) = \varphi\theta, \tag{18}$$

where $\varphi \in \mathbb{R}^{p\times l}$ is the regressor fuzzy basis function expressed as,

$$\varphi = \frac{\left(\prod_{i=1}^{m} \mu_F(\tilde{x}_i)\right)}{\sum_{l=1}^{N} \left(\prod_{i=1}^{m} \mu_F(\tilde{x}_i)\right)} \tag{19}$$

θ is the parameter vector; $\theta = \left[\Gamma^1, \Gamma^2, \ldots, \Gamma^l\right]^T \in \mathbb{R}^l$. The existence of nonlinearity in the system,

$$\Xi(\chi, \breve{u}) = \Xi(\chi, u_{servo} + u_{fz} + \rho\kappa) \tag{20}$$

can be compensated by the following fuzzy controller,

$$u_{fz} = u_{fz}(\chi, \breve{u}) + \delta = \varphi\hat{\theta} + \delta \tag{21}$$

where δ is the approximation error. Equation (16) can be written in the following form,

$$\dot{\varepsilon} = A_{cl}\varepsilon + b\left[\Upsilon + \left(u_{fz}(\chi, \tilde{\theta}) - u_{fz}(\chi)\right) - \rho\kappa\right] \quad (22)$$

where $\Upsilon = \Xi(\chi, \breve{u}) - \Xi(\chi, u)$ and $\tilde{\theta} = \theta - \hat{\theta}$. $\hat{\theta} \in \mathbb{R}^l$ is the estimate of the true parameter θ and $\tilde{\theta}$ is the corresponding parameter estimation error vector.

Theorem 1: Let the control signal to control the temperature of a CSTR plant system in (2) be defined as $u = u_{servo} + u_{fz} - \rho\kappa$, where u_{servo} is the control signal to track the desired trajectory of the desired temperature, and $u_{fz} = \varphi\hat{\theta}$ is the adaptive fuzzy compensation controller, through which $\hat{\theta}$ is generated by the following gradient adaptive law,

$$\dot{\hat{\theta}} = \gamma_\theta \varphi^T b^T P\varepsilon - \gamma_\theta\sigma_\theta\hat{\theta} \quad (23)$$

and the robustification signal can be expressed as follows,

$$\kappa = \frac{\varepsilon}{\|\varepsilon\|} \quad (24)$$

where γ_θ is the positive constant to be designed later and σ_θ is the positive design constant. Then, the tracking error pair $(\varepsilon, \tilde{\theta})$ signals will converge to a small compact set in finite time.

Proof: Let us consider the following positive-definite function,

$$V = V_e + V_\theta \quad (25)$$

where $V_e = \frac{1}{2}\varepsilon^T P\varepsilon$ *and* $V_\theta = \frac{1}{2\gamma_\theta}\tilde{\theta}^T\tilde{\theta}$.

$\varepsilon \in \mathbb{R}^n$ is the tracking error vector and P is positive definite symmetric matrix to be designed as in (14).

Differentiating (25) with reference to time yields

$$\begin{aligned}\dot{V} &= \frac{1}{2}\left(\varepsilon^T P\dot{\varepsilon} + \dot{\varepsilon}^T P\varepsilon\right) + \frac{1}{2\gamma_\theta}\left(\tilde{\theta}^T\dot{\tilde{\theta}} + \dot{\tilde{\theta}}^T\tilde{\theta}\right)\\ &= \frac{1}{2}\varepsilon^T P\left(A\varepsilon + b\left(\varphi\tilde{\theta} + \Upsilon - \rho\kappa\right)\right)\\ &\quad + \left(A\varepsilon + b\left(\varphi\tilde{\theta} + \Upsilon - \rho\kappa\right)\right)^T P)\\ &\quad + \frac{1}{\gamma_\theta}\left(\tilde{\theta}^T\dot{\tilde{\theta}}\right)\\ &= \frac{1}{2}\varepsilon^T\left(PA + A^T P\right)\varepsilon + \left[\varepsilon^T Pb(\varphi\theta + \Upsilon - \rho\kappa)\right]\\ &\quad + \frac{1}{\gamma_\theta}\left(\tilde{\theta}^T\dot{\tilde{\theta}}\right)\end{aligned} \quad (26)$$

Observing (25) and $\dot{\tilde{\theta}} = -\dot{\hat{\theta}}$ *(due to* $\dot{\theta} = 0$*) while considering the adaptive law in (26) gives*

$$\begin{aligned}\dot{V} &= -\frac{1}{2}\varepsilon^T Q\varepsilon + \varepsilon^T Pb\left[\varphi\tilde{\theta} + \Upsilon - \rho\kappa\right] - \frac{\sigma_\theta}{\gamma_\theta}\tilde{\theta}^T\dot{\hat{\theta}}\\ &= -\frac{1}{2}\varepsilon^T Q\varepsilon + \varepsilon^T Pb\left[\varphi\tilde{\theta} + \Upsilon - \rho\kappa\right]\\ &\quad - \sigma_\theta\left(\tilde{\theta}^T\varphi^T b^T P\varepsilon - \tilde{\theta}^T\hat{\theta}\right)\end{aligned} \quad (27)$$

Under the notion that $\rho = \rho_1 + \rho_2$ with $\|\rho_1\| \gg \|\rho_2\|$ where $\|\rho_2\| > 0$, the controller term ρ_2 is selected such that

$$\|\rho_2\|\frac{\varepsilon}{\|\varepsilon\|} > \|\Upsilon\| \quad (28)$$

Then,

$$\dot{V} = -\frac{1}{2}\varepsilon^T Q\varepsilon - \varepsilon^T Pb\rho_1 + \sigma_\theta\tilde{\theta}^T\hat{\theta} \quad (29)$$

Expanding the term $\tilde{\theta}^T\hat{\theta}$,

$$\tilde{\theta}^T\hat{\theta} = \tilde{\theta}^T\left(\bar{\theta} - \tilde{\theta}\right) = \tilde{\theta}^T\bar{\theta} - \tilde{\theta}^T\tilde{\theta} \quad (30)$$

and completing the square in (30),

$$\tilde{\theta}^T\bar{\theta} - \tilde{\theta}^T\tilde{\theta} = -\frac{1}{2}\tilde{\theta}^T\tilde{\theta} + \frac{1}{2}\bar{\theta}^T\bar{\theta} \quad (31)$$

Taking the upper bound of (29) yields

$$\begin{aligned}\dot{V} \leq &-\frac{1}{2}\lambda_{\min}(Q)\|\varepsilon\|^2 - \lambda_{\min}(P)b\|\varepsilon\|\\ &-\frac{1}{2}\sigma_\theta\left\|\tilde{\theta}\right\|^2 + \frac{1}{2}\sigma_\theta\left\|\bar{\theta}\right\|^2\end{aligned} \quad (32)$$

where $\lambda_{\min}(\cdot)$ *and* $\lambda_{\max}(\cdot)$ *denote the minimum and maximum singular values of a matrix, respectively.*

According to the Rayleigh principle, it is to note that,

$$\frac{1}{2}\lambda_{\min}(P)\|\varepsilon\|^2 \leq V_\varepsilon \leq \frac{1}{2}\lambda_{\max}(P)\|\varepsilon\|^2 \quad (33a)$$

$$\frac{1}{2}|\gamma_\theta|\left\|\tilde{\theta}\right\|^2 \leq V_\theta \leq \frac{1}{2}|\gamma_\theta|\left\|\tilde{\theta}\right\|^2 \quad (33b)$$

Therefore, from (32),

$$\dot{V} \leq -\mu_\varepsilon V_\varepsilon - \breve{\mu}_\varepsilon\sqrt{V_\varepsilon} - \mu_\theta V_\theta + \Omega \quad (34)$$

where $\mu_\varepsilon = \frac{1}{2}\frac{\lambda_{\min}(Q)}{\lambda_{\max}(P)}$, $\breve{\mu}_\varepsilon = \sqrt{\frac{1}{2}\frac{\lambda_{\min}(Q)}{\lambda_{\max}(P)}}$, $\mu_\theta = \frac{1}{2}\frac{\sigma_\theta}{\gamma_\theta}$ denote the rate of convergence for the error pair $\left(\varepsilon, \tilde{\theta}\right)$. Ω is the invariant set, which depends on the value of $\bar{\theta}$ (true value of the parameter estimates); i.e., $\Omega := \{\bar{\theta} \in \mathbb{R}^l | \bar{\theta}^T\bar{\theta} - M^2 > 0\}$, where $M > \left\|\tilde{\theta}\right\|$. Thus, the result in (34) implies that the error pair $\left(\varepsilon, \tilde{\theta}\right)$ signal will converge to a compact set in finite time bounded by Ω.

IV. SYNTHESIS OF THE FUZZY ADAPTIVE CONTROL LAW

A. ALGORITHM FORMULATION

An adaptive Mamdani-type fuzzy inference scheme to enhance the conventional PID control of [12] has been developed in this paper. The benefit of this approach is that the design has better coverage for wide state variable patterns and simpler practical implementation. A fuzzy-type inference control structure is derived to smoothly interpolate the scheduled gains across the input state space. Accordingly, the adaptive fuzzy logic controller efficiently tunes the controller gains and compensates the hard nonlinearity of the CSTR model, which evolves around its dynamic operating trajectory. Then, a single fuzzy-based PID-type controller that is tuned according to an adaptive stable methodology is synthesized in this paper.

The control input of the PID regulator is adapted so that the feedback gains are adjusted through a fuzzy adaptive gain scheduler with the tracking error dynamic and its first derivative. The control strategy is depicted in Fig. (1).

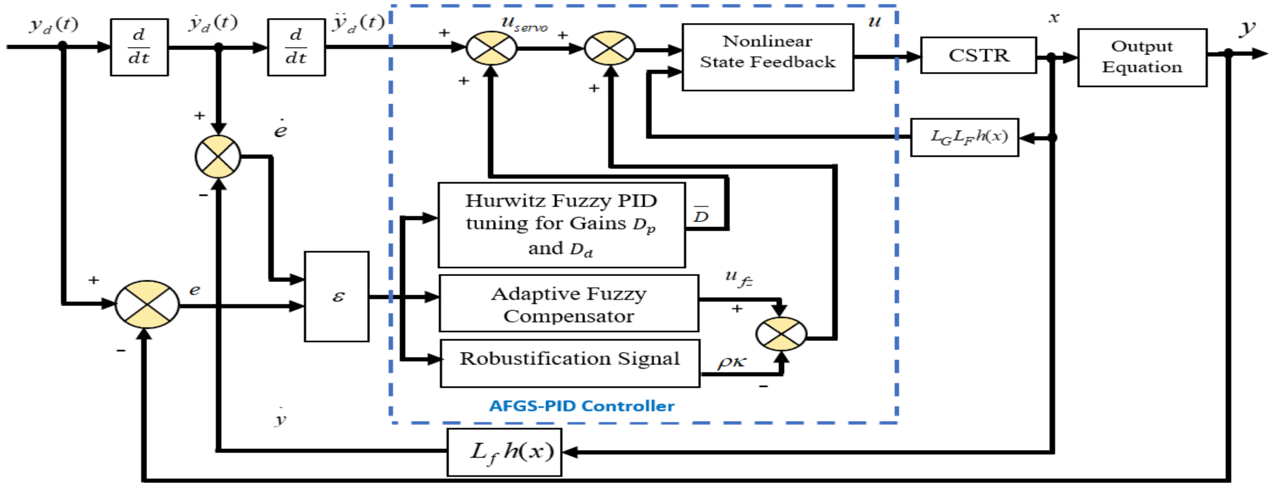
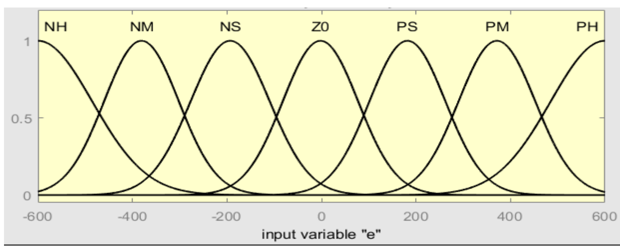
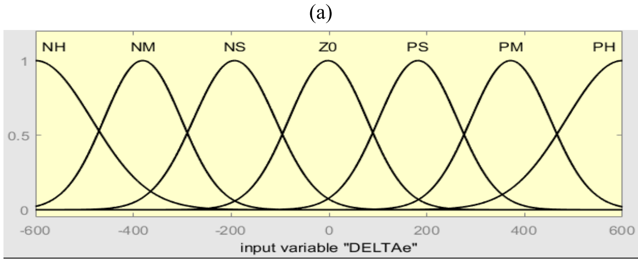


FIGURE 1. **Block Diagram of the proposed Nonlinear Adaptive Fuzzy PID Gain Scheduling Control (AFGS).**

Unlike the conventional PID or PD control, where static gains are provided through the expert knowledge (and experience) of the operator, fuzzy inference engine rules are defined to generate the control gains for u_{servo} while maintaining the $A_{cl} = A_0 - b\overline{D}$ Hurwitz. Each supervised gain is tuned with a stable adaptive scheme through the fuzzy sets, which are characterized by the membership functions presented in Figs. (2a) and (2b).



(a)



(b)

FIGURE 2. **(a) Gaussian Membership function for $e(d)$. (b) Gaussian Membership function for the $\Delta e(d)$ Implication process of a fuzzy rule.**

The adaptive fuzzy gain scheduling algorithm will be stated here. The formal definition of the 7-step routine is as follows:

- Calculate the control gains D_p and D_d are as presented in (11); obtain the tracking control input u_{servo} defined by

$$u_{servo} = -\overline{D}\varepsilon - \ddot{y}_d \tag{35}$$

where $\overline{D} = [D_p D_d]$; $\varepsilon = [e\ \dot{e}]$ and $\overline{D}$ satisfy that $A_{cl} = A - b\overline{D}$ is Hurwitz.

- Ascertain parameters D_p and D_d by a group of fuzzy statements as follows:
  If $e(d)$ is A_i and $\Delta e(d)$ is B_i, then D_p is C_i and D_d $=$ $G_i i = 1, 2, \ldots\ n$

Note that the gains A_i, B_i, C_i, and G_i are fuzzy settled gains on the matching associated rules. The fuzzy Gaussian membership functions rules for $e(d)$ and $\Delta e(d)$ are shown in Figs. (2a) and (2b). Here, P stands for 'positive', N for 'negative', Z for 'zero', M for 'medium', S for 'small', and H for 'high'. Therefore, PH denotes 'positive high', NM denotes 'negative medium', etc. Fuzzy values C_i and G_i can be 'Big or 'Small'. Likewise, the classes can be considered by membership functions in Fig. (3), where:

$$z = (D_p, or\ D_d) \tag{36}$$

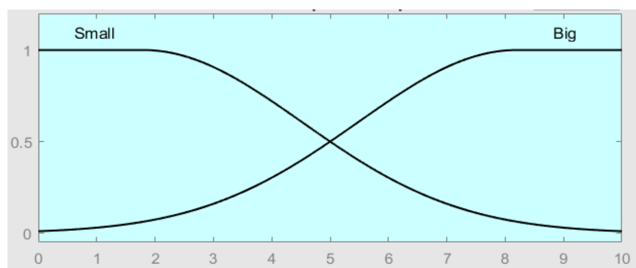


FIGURE 3. **Gaussian Membership function for D_p, D_d.**

and the rating coefficient μ of the fuzzy membership function is related as follows:

$$\begin{cases} \mu_{SMAL}(z) == -\dfrac{1}{4} ln(z)\ or\ z_{SMAL}(\mu) = e^{-4\mu} \\ \mu_{BIG}(z) == -\dfrac{1}{4} ln(1 - z) or z_{BIG}(\mu) = 1 - e^{-4\mu} \end{cases} \tag{37}$$

- Perform the control gain tuning rules as illustrated in Tables 2 and 3. The reader can find a detailed

TABLE 2. Fuzzy Associative Memory (FAM) for D_p.

		$\Delta e(d)$						
		NH	NM	NL	Z	PL	PM	PH
$e(d)$	NH	B	B	B	B	B	B	B
	NM	S	B	B	B	B	B	S
	NL	S	S	B	B	B	S	S
	Z	S	S	S	B	S	S	S
	PL	S	S	B	B	B	S	S
	PM	S	B	B	B	B	B	S
	PH	B	B	B	B	B	B	B

TABLE 3. Fuzzy Associative Memory (FAM) for D_d.

		$\Delta e(d)$						
		NH	NM	NS	Z	PS	PM	PH
$e(d)$	NH	S	S	S	S	S	S	S
	NM	B	B	S	S	S	B	B
	NS	B	B	B	S	B	B	B
	Z	B	B	B	B	B	B	B
	PS	B	B	B	S	B	B	B
	PM	B	B	S	S	S	B	B
	PH	S	S	S	S	S	S	S

description of the exploited method to define the universe of discourse for $e(d)$, $\Delta e(d)$, D_p and D_d in [12].

- Apply the defuzzification formulas to obtain:

$$D_p = \sum_{i=1}^{m} \mu_i D_{pi} = 1$$
$$D_d = \sum_{i=1}^{m} \mu_i D_{di} = 1 \quad (38)$$

- Calculate the adaptive fuzzy compensator control law u_{fz} through the fuzzy logic controller, which satisfies:

$$u_{fz} = \varphi \hat{\theta} \quad (39)$$

where φ is defined by (19), and $\hat{\theta}$ is obtained by using (23).

- Define the robustification signal $\rho\kappa$ using (22).
- Express the adaptive scheduling control input as:

$$u = u_{servo} + u_{fz} - \rho\kappa \quad (40)$$

B. COMPARATIVE SIMULATION RESULT

To evaluate the performance of the designed scheme on a nonlinear CSTR plant, as described in (1), the parameters in [30] are adopted. The fuzzy adaptive controller was analyzed for the product temperature $x_2 = T$ coolant flow rate tracking via the control input $u = Q_c$ when the product concentration should reach a constant value with a small time constant. Figs. (4) and (5) illustrate the required product temperature tracking trajectory using the AFGS-PID for the 3rd-order CSTR process. Recall the controller structure in Section III, the designed control inputs are composed of u_{servo}, the control signal that is responsible for tracking, u_{fz}, which is the adaptive fuzzy-based compensator that estimates the input-output nonlinear model of the plant, and $\rho\kappa$, which is the robustification signal that assists the control action by rejecting the bounded disturbance through the sliding-mode control element. Elements D_p and D_d in u_{servo} are generated by the fuzzy engine (see the corresponding FAM in Table 2 and Table 3) based on the tracking error. The double differentiation of the trajectory is required in u_{servo} to allow future anticipation during the tracking. Figs. (4)-(6) show the interesting tracking performance and satisfactory behavior of the control design. Indeed, although the quick step variation on the desired output trajectory has a large gap deviation, the real output trajectory was overdamped with a reduced settling and rising time. The accuracy of the response is quite satisfactory along the desired trajectory. Considering the selected key performance indicator (Y_{os} is the maximum overshoot, T_5 is the five-percent settling time, ISE is the integral of the square error, and IAE is the integral absolute error), the proposed AFGS-PID obviously outperforms the other three controllers.

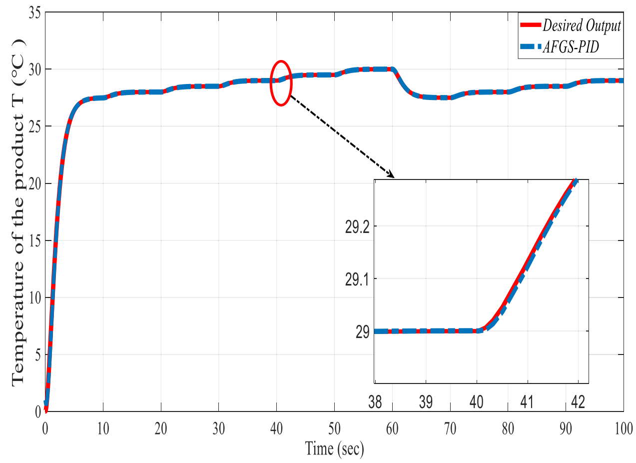


FIGURE 4. Trajectory tracking using the AFGS-PID Controller.

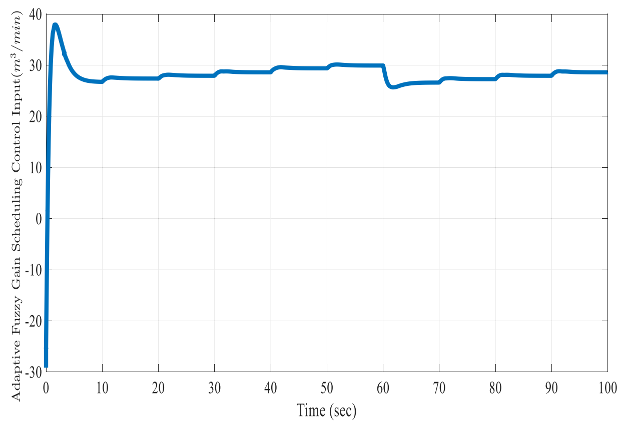


FIGURE 5. AFGS Control input.

V. A COMPARATIVE PERFORMANCE ANALYSIS FOR THE PEER PID-BASED CONTROL METHODS

The conventional PID control is most extensively exploited to control nonlinear industrial plants. Adjusting the PID gains is

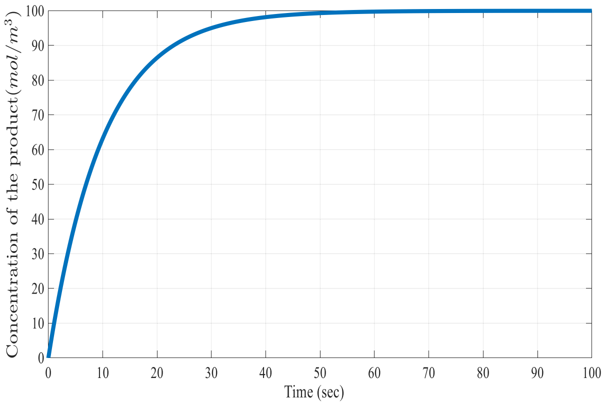


FIGURE 6. Dynamic of the Product Concentration.

an imperative step to obtain the optimal closed-loop performance (reduced overshooting, small rising time, small settling time, peak time below 15%, and minimized steady-state error). This section compares different PID tuning techniques (AFGS-PID, FGS-PID [12] and conventional PID-based control) for the CSTR model and analyzes the faced weakness and strengths for all approaches. These quantities are designed and evaluated regarding the performance of ISE and IAE. The achievements of several adjustment techniques and various tuning methods are detected and analyzed by implementing a quick variable step input signal to the studied process.

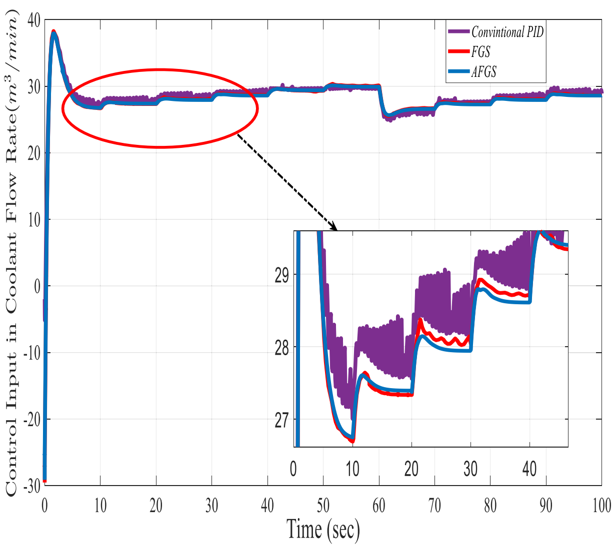


FIGURE 7. Control input signal of the proposed AFGS-PID against other controllers.

The output trajectory tracking performances of all three controllers are illustrated in Figs. (8) and (9). The control inputs from all three controllers are shown in Fig. (7). Table 4 summarizes the comparison data for different control schemes. The proposed AFGS-PID control is better than the other two control schemes. Indeed, no overshooting can be detected in any step change of the input trajectory.

TABLE 4. Comparative Summary of the Controller Performance.

Control	IAE	ISE	Settling time	Y_{os}	T_5	Rise time
AFGS	1.12	0.25	3.8 m	0.01%	0.1	3.55 s
FGS	1.69	1.3	6.1 m	0.04%	0.3	5.31 s
PID	3.05	1.99	18.5 m	8%	4.1	7.57 s

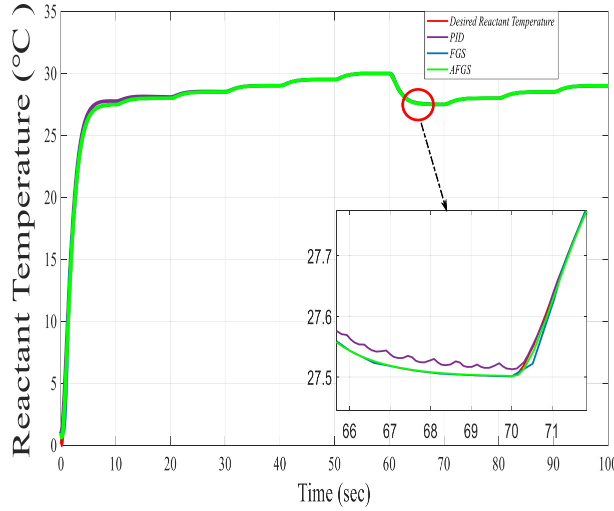


FIGURE 8. Output trajectory tracking for different control strategies when the step temperature decreases.

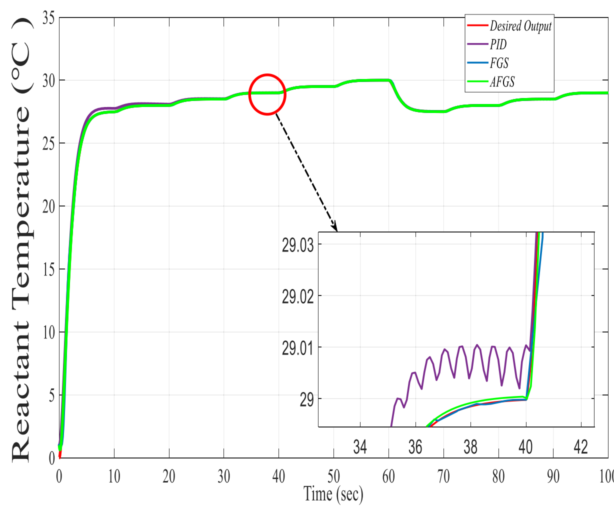


FIGURE 9. Output trajectory tracking for different control strategies when the step temperature increases.

The tracking error is substantially reduced along the overall output trajectory. The adaptive tuning for the integral gain considerably improved the global performance in terms of swiftness and accuracy. Moreover, the stability is analytically proven, which is empirically construed for the fuzzy and conventional PID approaches.

VI. CONCLUSION

In this work, an original advanced adaptive control methodology has been proposed for a benchmark model of a CSTR. This model is characterized by unstable nonlinear dynamics when the operating level changes. The designed control structure is composed of the fuzzy logic PID-based controller, in which the gains are monitored and scheduled through an adaptive stabilizing block. Without specific presumptions about the level of variations of the CSTR dynamics, a stable adaptive regulator is presented with the design and stability analysis proof for the closed-loop system and accurate asymptotic tracking for the desired output trajectory. The achievements of the AFGS-PID controller were proven based on a simulation study. A comparative study between peer control schemes and the suggested AFGS-PID, which uses the gain scheduling methodology, confirms the efficiency of the AFGS-PID controller for a nonmonotonic operating trajectory. The main benefits of the developed solution with respect to peer solutions are conferred by the design of the reinforced scheme, as determined by a rigorous analytical stability analysis.

The addressed approaches in this paper constitute a substantial control database for designing a big data control technique for the fault tolerant control of the CSTR model. The future work will investigate the effect and behavior of this technique in the case of a disturbance occurrence for the CSTR state variables. An analytical closed-loop output trajectory analysis for the asymptotic stability will be considered.

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