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Tracking Control of a Continuous Stirred Tank Reactor Using Advanced Control Algorithms

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Abstract— **The Continuous Stirred Tank Reactor (CSTR) is a common type of industrial equipment used in chemical processes with second-order nonlinear dynamics. CSTR is a nonlinear and linked nature makes it challenging to develop a robust control with a bigger operating zone. In the process industry, a CSTR is a crucial component. It serves as a foundation for studying and controlling other chemical reactors. Good state estimation and disturbance rejection are required in industrial processes. The most important characteristic for CSTR operation is temperature. The behavior is obtained by steady-state and dynamic analysis of the model which is usually represented by a set of differential equations. An event-based Neural network, Model Predictive Control (MPC), and Model Reference Adaptive Control (MRAC) controller are presented in this work to provide robustness to the system with the added benefit of conserving energy expenditure under parameter variations and fast changing dynamics. Numerical simulations were used to confirm the controller's robustness and efficacy. In comparison to the ANN and MPC, the simulation results clearly show that the MRAC technique delivers appropriate performance in terms of process functional improvements, more flexibility, and improved system-tracking precision in control action.**

Index Terms: **ANN, CSTR, Lyapunov, MPAC, MPC.**

I. INTRODUCTION

Stirred tank reactors are commonly employed in industry, particularly in the chemical and biochemical industries. In almost every facility in the chemical and materials industries, reactors are utilized to transform basic raw materials into products. Nonlinearities can have a negative impact on chemical plants, hence a control method to cancel them out is essential. Due to their nonlinearity chaotic behavior and the presence of numerous stable and unstable equilibrium points, chemical reactors pose a difficult control problem. Because the input flow of the reactant or cooling liquid can be easily adjusted, CSTR is commonly utilized for control. Reactions that convert reactants to products result in a wide range of useful and necessary objects. Chemical reactors are necessary for modern civilization's safe, efficient, and consistent operation [1]. The CSTR mathematical model [2] describes the interaction between state variables within the reactor that are dependent on material or heat balances. Because of its nonlinear dynamic, the subject of temperature regulating CSTR is seen as an intriguing and contentious topic, particularly among control professionals. The great majority of traditional controllers are designed for linear time-invariant systems [3]. According to this study, the CSTR's two outputs are the temperature of the reactor and the concentration of the reactant in the tank, with the coolant or jacket temperature being the adjustable variable. The control goals of this work are to develop a controller that controls CSTR temperature and preserves process stability while suppressing the effects of external disturbances using supervisor neural networks controllers, Model Predictive Control (MPC), and Model Reference Adaptive Control (MRAC)-based Lyapunov theory. Performed a comprehensive analysis based OID for CSTR presented in [4]. Optimal linear control techniques based on linearization have also been developed to assure the stability of continuously stirred tank reactors [5]. With H_2 and H_∞, [6] presents a robust resilient design technique for linear and nonlinear CSTR models. [7] presents design methodologies based on a variety of models and strategies based on a blend of neural networks and model predictive control. The following is a description of the structure of the paper: In Section II, the CSTR model dynamics are explained. The control design methodology is presented in Section III. In section IV, numerical simulations are demonstrated. There is a conclusion in section V.

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II. DYNAMIC MODEL OF CSTR

A process model is a set of equations that can be used to predict the behavior of a chemical reaction. Internal balances are employed to derive the CSTR mathematical formulation; it's worth noting that the reactor is enclosed in a jacket that divides the feed and exhaust streams. By transferring the energy through the reactor walls and into the jacket, the heat generated by the reaction is dispersed. The goal is to maintain an acceptable temperature in the reacting mixture T. The following assumptions were used to develop modeling equations for a CSTR based on Ref [8,9]. Inside the reactor, there is optimum mixing, and the reactor's characteristics and volume are constant. The manipulated variable is the cooling jacket temperature T_j as presented in Figure. 1.

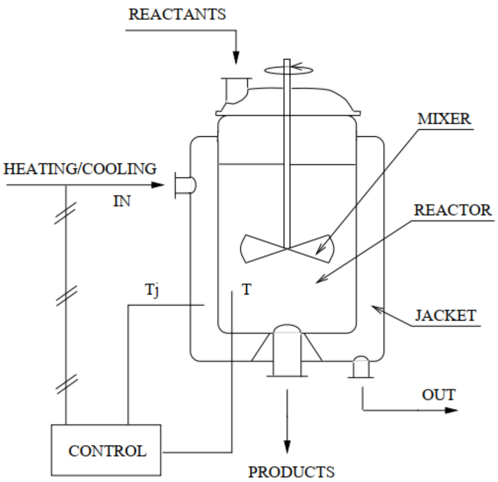


Figure 1. Process flow of CSTR with cooling jacket [8]

To build the mathematical model for this process, mass and energy balances are done, and appropriate constitutive equations are added [8,9].

A. Mass Balance

The following is the general equation for a mass

$$V\frac{dC_A}{dt} = F(C_{AF} - C_A) - V(-r_A) \quad (1)$$

$$V\frac{dC_A}{dt} = F(C_{AF} - C_A) - VK_0 \exp\left(\frac{-E_a}{R(T+460)}\right) C_A \quad (2)$$

Where

C_A: The concentration of product A in the reactor.
C_{AF} : The Concentration of A in the feed stream.
F: The volumetric flow rate of the feed
V: Volume of the tank.
r_A: Rate of reaction per unit volume.
K_0: Reaction rate constant.

The following equation [8] may be used to calculate the rate of generation of moles in the system:

$$\frac{dC_A}{dt} = \frac{F}{V}(C_{AF} - C_A) - K_0 \exp\left(\frac{-E_a}{R(T+460)}\right) C_A \quad (3)$$

B. Energy balance

The following is a generic equation for an energy balance in CSTR:

$$Vp C_P \frac{dT}{dt} = C_P F(T_F - T) + V\Delta H(r_A) + UA\left(T - T_j\right) \quad (4)$$

Where

T: The temperature reactor.
T_F: The feed temperature.
E_a: activation energy.
R: ideal gas constant.
C_P: Heat capacity.
ΔH: Heat of reaction
UA: Overall heat transfer
$\rho * C_p$: Density*Heat capacity

$$V\Delta H(-r_A) = (-\Delta H)\, VK_0 \exp\left(\frac{-E_a}{R(T+460)}\right) \quad (5)$$

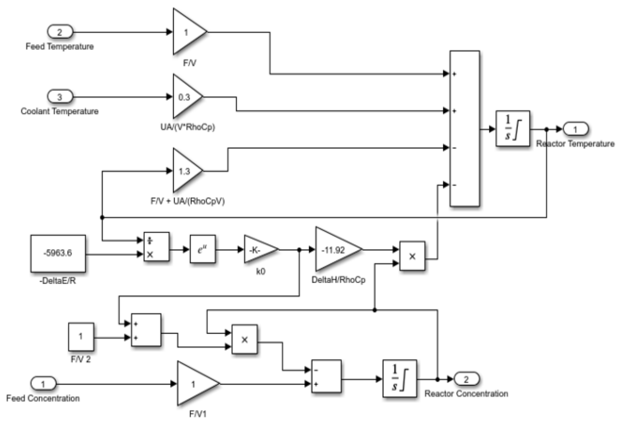
The final equation becomes

$$\frac{dT}{dt} = \frac{F}{V}(T_F - T) - \left(\frac{\Delta H}{pC_P}\right) K_0 \exp\left(\frac{-E_a}{R(T+460)}\right) C_A - \frac{UA}{VpC_P}\left(T - T_j\right) \quad (6)$$

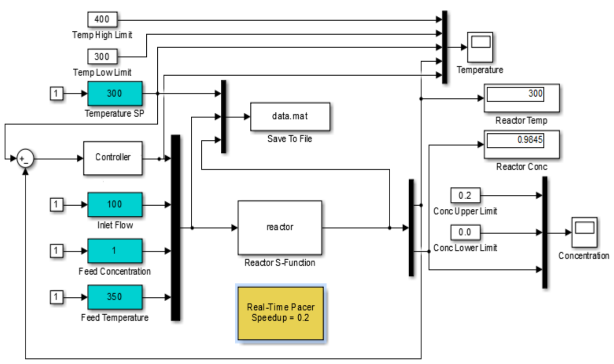
The parameters that will appear in the CSTR modeling equations are listed in Table 1. Figures 2 show the Simulink model and S- function of CSTR process. Figure 3 depicts the temperature and concentration outputs open loop responses. According to the open loop response, the CSTR process output never reaches the set points, and the dynamic behavior of the CSTR process varies at different operating points. To reduce error and improve transient responsiveness, a controller must be built.

Table 1. Parameters of CSTR Model [8]

Reactor parameters	Values	Units
E_a	32400	BTU/lbmol
K_0	15×10^{12}	h^{-1}
ΔH	-45000	BTU/lbmol
UA	75×1221	BTU/h-F
$\rho * C_p$	53.25	BTU/ft^3
R	1.987	BTU/lbmol-F
V	750	ft^3
F	3000	ft^3/h
C_{AF}	0.132	Lbmol/ft^3



a. Simulink model of CSTR



b. S-function of CSTR

Fig. 2. Simulink model and S-function of CSTR

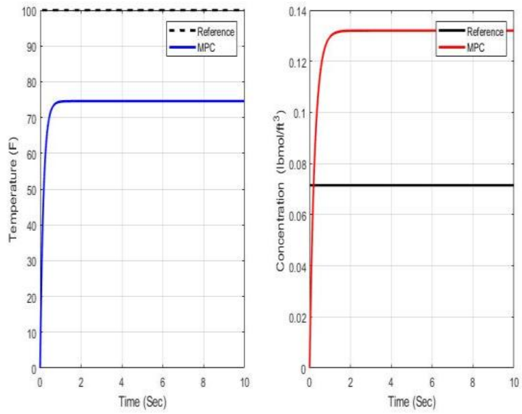


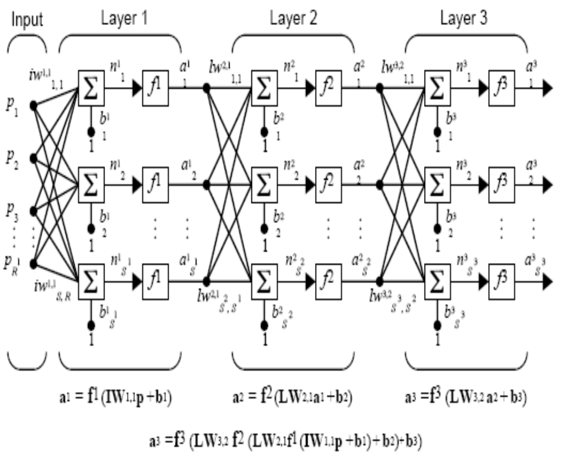
Figure. 3. Temperature and comcentration response of open loop CSTR

III. CONTROL DESIGN METHODOLOGY

The temperature is the "dominant variable" in many chemical reactors. The term "dominating variable" refers to a factor that has a significant impact on the reactor's economics, quality, safety, and operability. This section covers the design of a temperature controller. The coolant or jacket temperature is the only controlled variable in CSTR, and the reactor temperature and reactant concentration in the tank are the only two outputs. The controller design for the system is evaluated using various controller approaches, including Design ANN Controller Based Supervised Control, design Model Predictive Control (MPC) and design Model Reference Adaptive Control (MRAC).

A. Design ANN Controller Based Supervised Control

Artificial neural networks (ANN) mimic the way neurons in human brain function. They are made up of multiple layers of artificial neurons that are connected to one another. Each layer in Figure. 4 has a number of P inputs. Each input is given a weight W, which is combined with a bias B to get the total equation PW + B. The sum equation is used to calculate the output, which is then fed into an activation function. Training methods are employed to train the ANN, which alters the weight W according to a cost function. Backpropagation is a common method for reducing error by changing the weights by computing the function's gradient [9].



Figurer 4. ANN structure

When employing ANN in control, there are two basic steps: system identification and control design. This control's identification stage entails training a neural network to display the plant's forward dynamics. For the model approximation, a neural network model of the plant that has to be controlled is created using two sub-networks. The following is the neuronal model:

$$y(t+d) = f[y(t), \dots, y(t-m+1), u(t-1), \dots\dots, u(t-n+1)] \quad (7)$$

where y(t) is the system output, u(t) is the system input and d is the relative degree ($d \geq 2$). Multilayer neural networks can be used to identify the function F. The identification model has the form:

$$\hat{y}(t+d) = f[y(t), .., y(t-m+1,\ u(t-1), .. u(t-n+1)] + g[y(t), , y(t-m+1, u(t-1), \dots u(t-n+1)]. u_{NN}(t) \quad (8)$$

Where $\hat{y}(t+d)$ is the estimate of $y(t+d)$. Identification is carried out at every instant t by adjusting the parameters of the neural network using the error $e(t) = y(t) - \hat{y}(t)$. For a system output, y(t+d) is used, and for a reference trajectory y_r(t+d). f and g are activation functions of the hidden layer, where the input units are only buffer units which pass the signals without changing them. The output unit is linear units. The hidden units are non-linear Polywog wavelet activation functions, as shown in Figure 5.

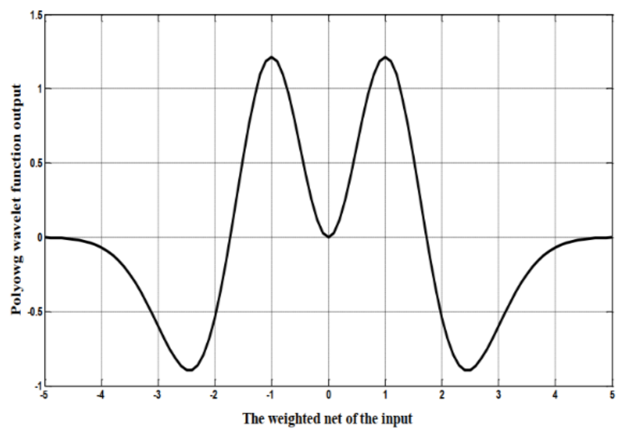


Figure 5: Polywog wavelet function

For each sub-network, the linear activation function uses the output layer. The controller output will have the form:

$$u(t) = \frac{y_r(t+d) - f[y(t), \dots, y(t-m+1, u(t-1), \dots u(t-n+1)]}{g[y(t),, y(t-m+1, u(t-1), \dots, u(t-n+1)]} \quad (9)$$

Using an existing controller, it is possible to teach a neural network the correct actions. Supervised learning is the term for this form of control. But why would we want to duplicate an already-functioning controller? The operational point is at the heart of most classic controllers. This means that if the plant operates around a given point, the controller will work well. If there is any ambiguity or change in an unknown plant, these controllers, such as PID controllers, will fail. The benefits of neuro-control include that if there is an uncertainty in the plant, the ANN can modify its settings and continue to operate the plant when other robust controllers would fail.

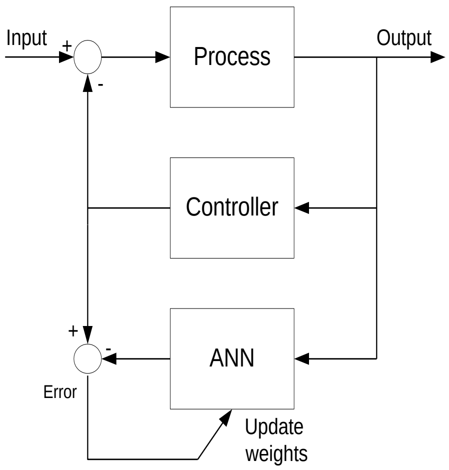


Figure. 6: Supervised learning using an existing controller

In supervised control, a teacher instructs the neural network on how to learn the proper actions (Fig. 6). The targets are provided by an existing controller during offline training, and the neural network adjusts its weights until the ANN's output is identical to the controller's. The neural network is placed in the feedback loop after it has been trained. The ANN should be able to regulate the process because it was trained using the existing controller targets. At this point, the process is controlled by an ANN, which works in the same way as the present controller. The ability to be adaptive online is the true benefit of neuro-control (Fig. 7). The weights are adjusted online using an error signal (desired signal – real output signal). If the process encounters a big disturbance uncertainty, the large error signal is fed back into the ANN, which adjusts the weights to keep the system stable [2, 9].

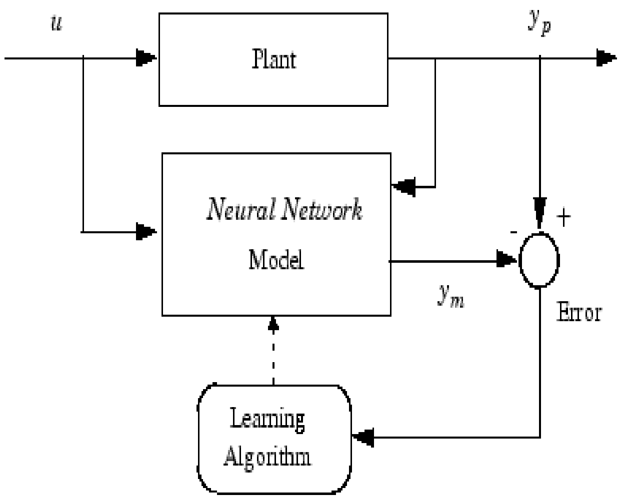


Figure. 7: Adaptive neural control

B. Model Predictive Control (MPC)

MPC is an advanced control method that may be used to solve challenging multivariable control issues. MPC displays its main strength when applied to problems with time delays, change performance and constrains controlled variables. In MPC, the fundamental control approach is to choose a set of future control called a control horizon and minimize a cost function based on the required target trajectory over a prediction horizon of a certain duration. The MPC approach is depicted in Figure. 8 where (P) is the prediction horizon and (C) is the control horizon. The future outputs (y(n+k) for k=1...P) of the system across a prediction horizon (P) are predicted at each instant using the process model and future inputs (u(n), u(n+1),..., u(n+C)). The system is programmed with a set of future inputs that minimize the objective function. Because a new output measurement might be present at the next sampling instant, just the first element of the future input is applied to the process. This operation is repeated with the addition of fresh measurements for the following sampling period, which is referred to as the receding approach. To create an MPC controller, the controlled variable's set point must be objectified. For any input and output, the value of the minimum and maximum weight restriction [10].

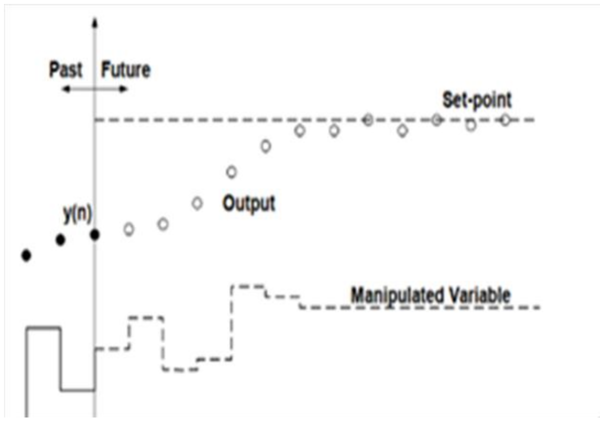


Figure 8. MPC Strategy [10]

MPC's basic structure is depicted in Fig. 9. A model is used to forecast future outputs based on the system's previous inputs and outputs. At each time step, a comparison is made between the plant's predicted output and the reference trajectory, and the plant's future errors are calculated. The optimizer determines the best future inputs while taking into account the objective function and constraints. The plant receives only the first element of this ideal set, and the cycle is repeated at the following sampling period.

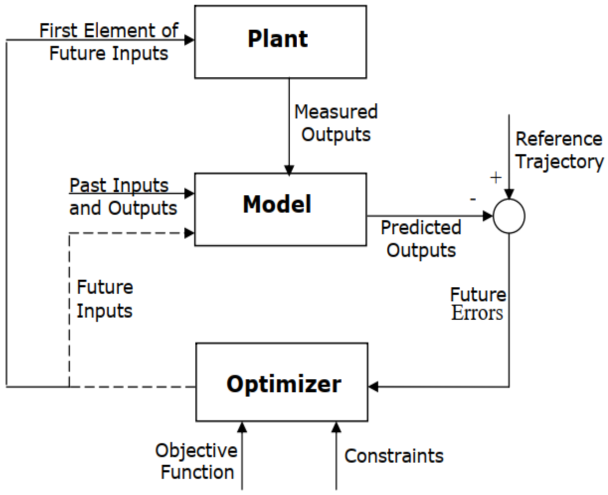


Figure. 9: Basic Structure of MPC

The benefit of a step response model is that the model coefficients may be determined from process input output data without assuming a model structure, and it can be used to any linear system.

A unit step is given to the system so as to obtain a process step response model. In Figure. 10, the $\mathbf{a_i}$ values are the step response coefficients and $\mathbf{h_i}$ values are the impulse response coefficients.

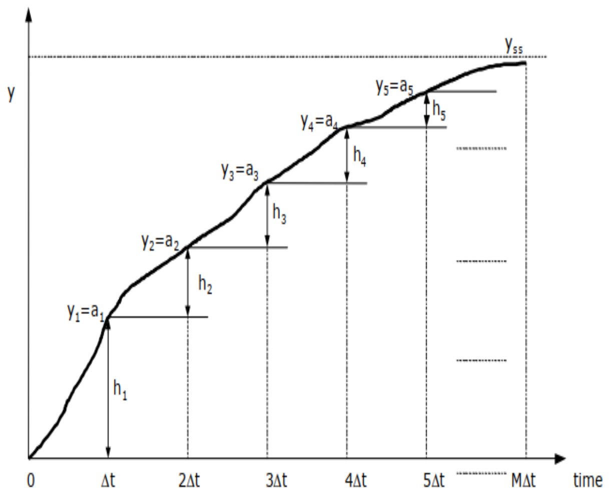


Figure 10: An Open Loop Step Response of a Linear Process

The step response coefficients are the summation of all impulse response coefficients as given in the following equation.

$$a_i = \sum_{j=1}^{i} h_i \quad (10)$$

The discrete convolution model using step response coefficients can be written as

$$\hat{y}_{n+1} = y_0 + \sum_{i=1}^{M} a_i \, \Delta u_{n+1-i} \quad (11)$$

In terms of the local predictive controller, a non-linear plant can be modelled by a locally linearized CARIMA model (Controlled Autoregressive and Integrated Moving Average Model) when addressing regulation regarding a specific operating point [10]:

$$A(q^{-1})y(t) = B(q^{-1})u(t-1) + C(q^{-1})\,\delta(t)/\Delta \quad (12)$$

where A and B are polynomials in the backward shift operator q^{-1_1}, Δ is the differencing operator 1- q^{-1}

$$A(q^{-1}) = 1 + a_1 q^{-1} + \cdots + a_{na} q^{-na}$$
$$B(q^{-1}) = b_0 + b_1 q^{-1} + \cdots + a_{nb} q^{-nb}$$

y(t) is the output and u(t) is the control input, if the plant has a non-zero dead-time, the leading elements of the polynomial $B(q^{-1})$are zero. and $\delta(t)$ is an uncorrelated random sequence. For simplicity, $C(q^{-1})$is chosen to be 1. The predictive control law's goal is to get future plant outputs y(t+j) as near to the desired reference y_r(t+j) as possible in order to minimize a cost function of the form:

$$J(N_1,N_2) = E\begin{Bmatrix} \sum_{j=N_1}^{N_2} [y(t+j) - y_r(t+j)]^2 \\ + \sum_{j=1}^{N_u} \delta(j)[\Delta u(t+j-1)]^2 \end{Bmatrix} \quad (13)$$

here N_1 and N_2 are the minimum and the maximum costing horizon, Nu is the Control horizon and l δ (j) is a control weighting sequence. Several SIMULINK models presented in MPC demonstration in MATLAB were used to create the steady state computations, dynamic behavior, and controller programming. In next section the adaptive controller based MRAC, which will be presented.

C. Model Reference Adaptive Control (MRAC)

Adaptive control techniques are system-theoretical tools for achieving closed-loop system stability and performance in the presence of system uncertainties. They are categorized as direct or indirect. Model reference adaptive control topologies are a well-known type of direct adaptive control technique as illustrated in figure. 11, these designs use two key components: a reference model and a parameter modification method. Where y_m(t) is the reference model's output signal and y(t) is the real plant's output signal. Two feedback loops exist in the system: one that includes the controller and the process, and another that modifies the controller settings. The parameters are tweaked based on error feedback. The conventional feedback loop is the inner loop, whereas the parameter adjustment loop is the outer loop. Lyapunov's stability theory can be used to establish the process for modifying the parameters in a MRAC [11]. The structure of MRAC Based on the Lyapunov rule is presented in figure. 12 [9,12].

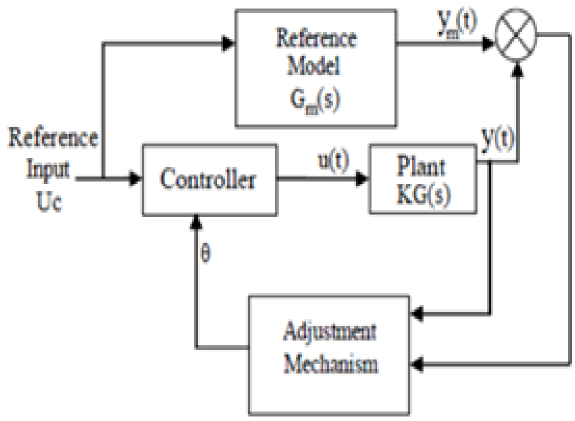


Figure. 11. Model Reference Adaptive Control [9,10]

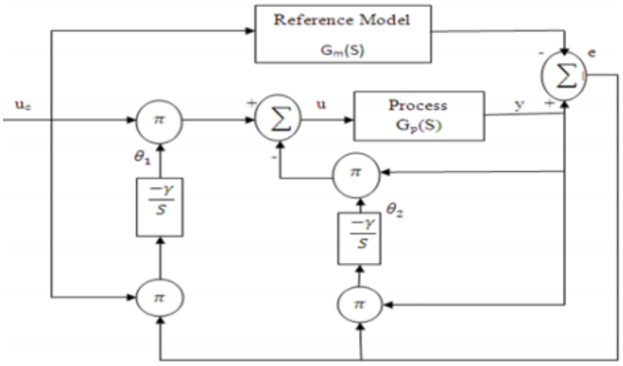


Figure 12. MRAC based on Lyapunov rule [9,11]

Typically, the reference model is considered to be a first-order system with the following differential equation [9]:

$$\frac{dy_m}{dt} = -a_m y_m + b_m u_c \qquad (14)$$

Where

y_m : The reference model's output.

u_c : The reference signal .

a_m , b_m : is desired constant.

A first order model is used to explain the process to be managed.

$$\frac{dy}{dt} = -ay + bu \qquad (15)$$

Where a, b is desired constant, y is the output of the plant and u is the input signal. Let the controller be

$$u(t) = \theta_1 u_c(t) - \theta_2 y(t) \qquad (16)$$

The values of the controller parameters (θ_1,θ_2) are determined by the reference input signal (u_c) as well as the error e(t).

$$e(t) = y(t) - y_m(t) \qquad (17)$$

Hence

$$\frac{de(t)}{dt} = -a_m - (b\theta_2 + a - a_m)y + (b\theta_1 - b_m)u_c \quad (18)$$

The error goes zero when the parameters

$$\theta_1 = \frac{b_m}{b} \qquad (19)$$

$$\theta_2 = \frac{a_m - a}{b} \qquad (20)$$

A quadratic function is used to ensure Lyapunov stability while the parameter modification process drives parameters $\theta_1$and θ_2 to their target values.

$$V(e,\theta_1,\theta_2) = \frac{1}{2}(e^2 + \frac{1}{b\gamma}(b\theta_2 + a - a_m)^2 + \frac{1}{b\gamma}(b\theta_1 - b_m)^2) \qquad (21)$$

This function is zero when e is zero and the controller parameters are equal to the correct values.

$$\frac{dV}{dt} = e\frac{de}{dt} + \frac{1}{\gamma}(b\theta_2 + a - a_m)\frac{d\theta_2}{dt} + \frac{1}{\gamma}(b\theta_1 - b_m)\frac{d\theta_1}{dt}$$

$$\frac{dV}{dt} = -a_m e^2 + \frac{1}{\gamma}(b\theta_2 + a - a_m)\left(\frac{d\theta_2}{dt} - \gamma y e\right) + \frac{1}{\gamma}(b\theta_1 - b_m)\left(\frac{d\theta_1}{dt} + \gamma u_c e\right)$$

(22)

The above-mentioned quadratic function is considered to be a Lyapunov function if the derivative is negative. Where γ is the adaptation gain. If the parameters are updated as

$$\frac{d\theta_1}{dt} = -\gamma u_c e$$

(23)

$$\frac{d\theta_2}{dt} = \gamma y e$$

(24)

and

$$\frac{dV}{dt} = -a_m e^2$$

(25)

As a result, negative semi-definite. As a result, V(t)≤V(0) and hence e ,$\theta_1$and θ_2 must be limited.

As a result, the y = e +y_mm system's output is also limited.

The adjustment law based on Lyapunov stability is given by

$$\frac{d\theta}{dt} = -\gamma e\theta \qquad (26)$$

The adaptation law discussed above is typically applied to the first or second system, but it has been demonstrated that it may be applied to a considerably broader variety of systems. As a consequence, unless the performance of the adaptation law is proved to be insufficient, a separate adaptation law does not need to be computed when switching to a different plant or model. The following equation gives the conventional form of the second-order system for the model reference [9,13].

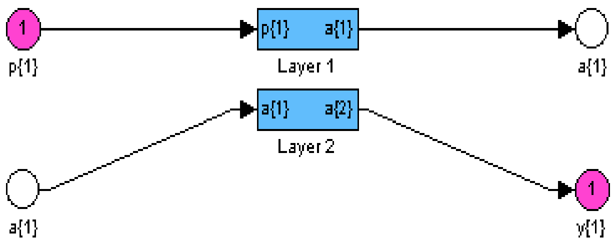
$$G_m(s) = \frac{\omega_n^2}{S^2 + 2\xi\omega_n S + \omega_n^2} \qquad (27)$$

Temperature control requirements include a maximum Overshoot (M_p) 5%, settling time (Ts) less than 1.7 seconds, and a steady-state error (Ess) less than 0.01. From the above specification, ξ =0.8 and ω_n=3 rad/s. As a result, the reference model's transfer function is

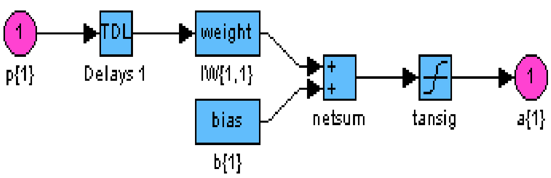
$$G_m(s) = \frac{9}{S^2 + 4.8s + 9} \qquad (28)$$

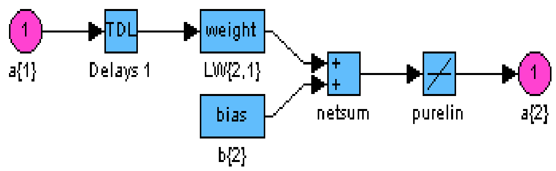
IV. SIMULATION RESULTS

The proposed ANN architecture is shown in Figure. 13. The neural network training parameters of NN are learning parameter = 0.45, moment term =0.25, iteration number 1500, Initial bias =0, Initial weights = 0 and hidden later neurons 7. The Resilient Back-propagation algorithm is used to adjust the weights of the neural network.



Model feedforward (FF) Neural Network





Two layers neural network

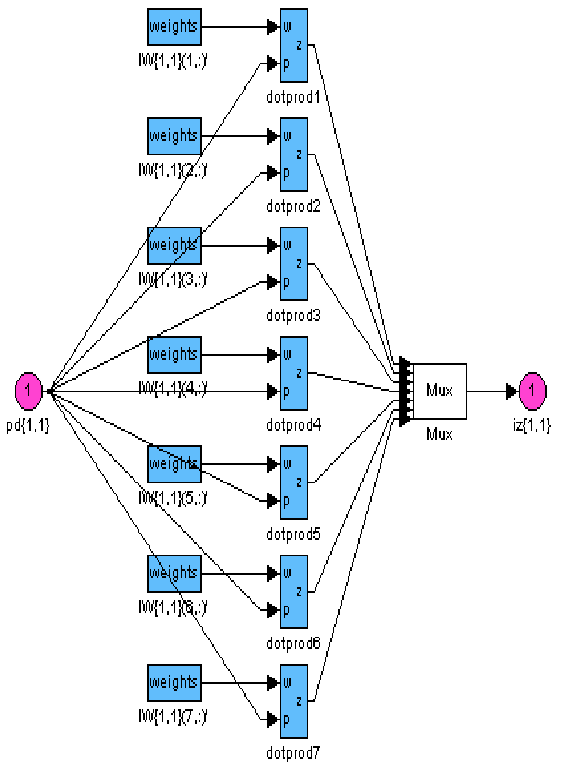


Figure 13. Structure feedforward (FF) neural network

The neural controller was trained to regulate the CSTR using a feedback controller based PID. The ability of the neural controller to track changes linked to the set-point has been det ermined through tests. The ideal structure of the neural controller was identified by a study of several structures utilizing 1000 input and output data. The mean square error of the multi-layer NN is depicted in the diagrams below (Figures. 14 and 15). The inaccuracy between the network and the output plant is considerable at the start of the training. The mean square error decreases as the number of epochs increases.

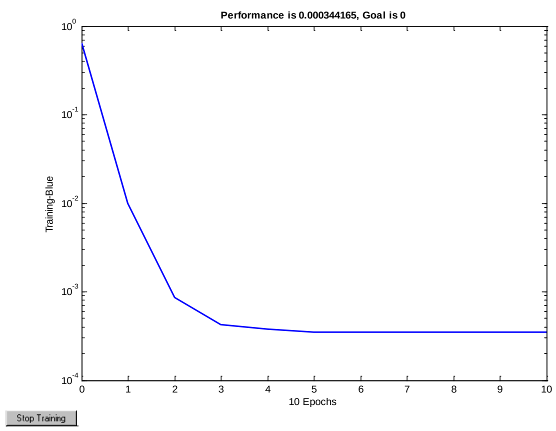


Figure 14.: The training temperature error decrease as the NN learns

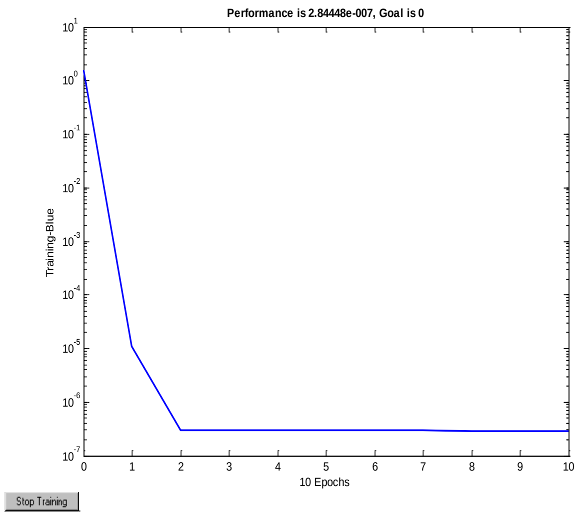


Figure 15. The training concentration error decrease as the NN learns

ANN, MPC and MRAC are all attached separately to the CSTR model that is built in the SIMULINK environment. The temperature and concentration responses when the ANN is applied to the system are offered in figure. 16. The results demonstrate that the system is stable and its transient responses are convenient.

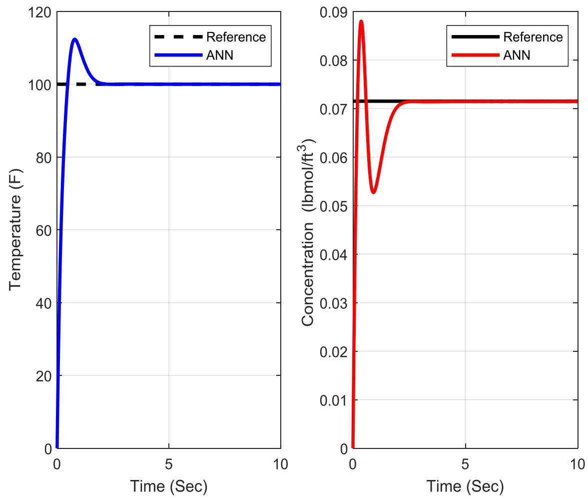


Figure 16. Temperature and concentartion responses of CSTR based ANN controller

The MPC for a (CSTR) designing using MPC Designer toolbox. The sample time, of 0.5 seconds, and with all other properties at their default values, including a prediction horizon of 10 steps and a control horizon of 2 steps. The temperature and concentration responses when the MPC is applied to the system are shown in fig. 17.

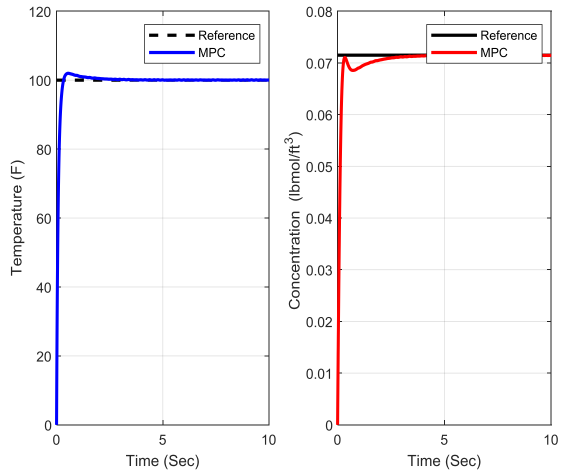


Figure 17. Temperature and concentartion responses of CSTR based MPC

The parameters of the MRAC controllers $\theta_1 = \frac{-100}{s}$, $\theta_2 = \frac{-100}{s}$ and the adaptation gain values $\gamma = 100$. The temperature and concentration responses when the MRAC is applied to the system are shown in figure. 18 [9].

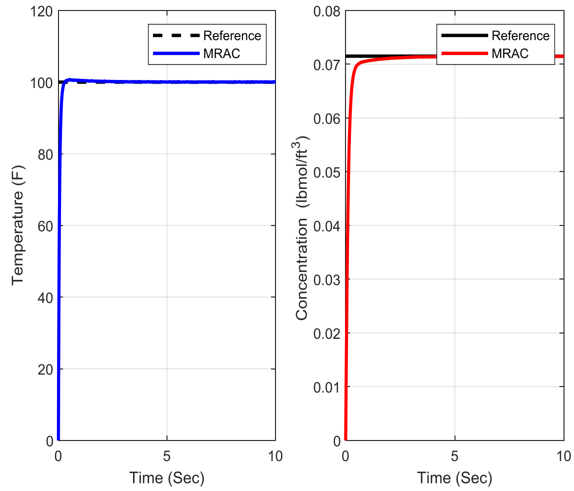


Figure 18. Temperature and concentartion response of CSTR based MRAC

MRAC is superior to MPC and ANN controller in terms of simulation results. Here, the designed controllers are tested when there is an external disturbance to the system. As shown in figure. 19 to figure. 21. The adaptive controller has more ability and effectiveness to reject the influence of noise compared with MPC and ANN controllers.

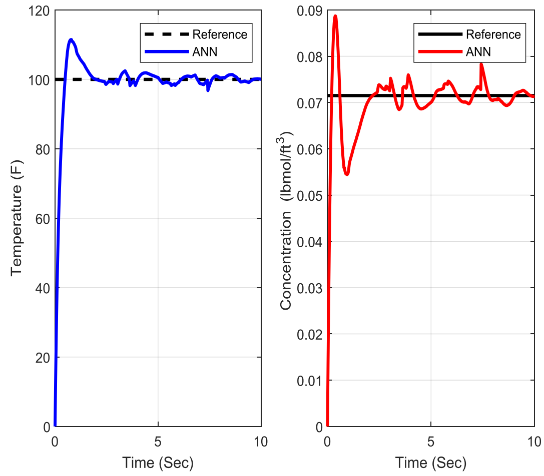


Figure 19. Temperature and concentartion response of CSTR based ANN controller with noise signal

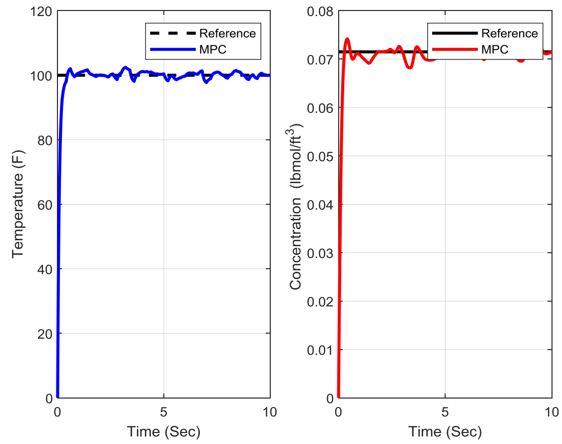


Figure 20. Temperature and concentartion response of CSTR based MPC controller with noise signal

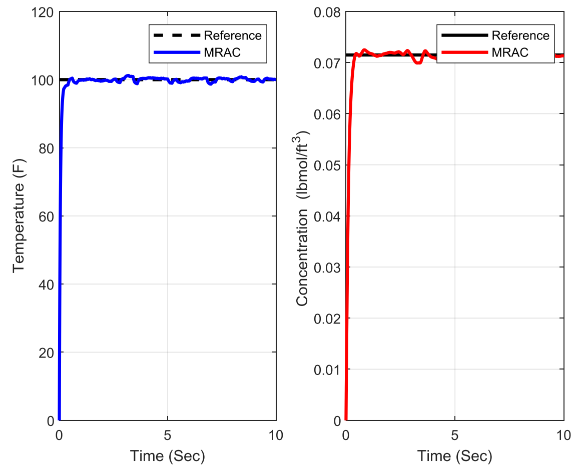


Figure 21. Temperature and concentartion response of CSTR based MRAC controller with noise signal

Figure 22 and 23 present the tracking responses of CSTR for different desired level. The performance of this system with both controllers has been compared and the result is presented in Table 2. From the previous results, we can draw that, the adaptive controller is robust and provides temperature control for CSTR with optimum performance. Figure 24. present the cost function for different controllers.

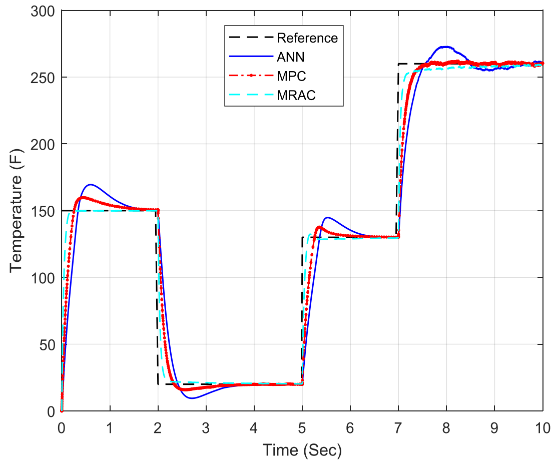


Figure 22. Tracking temperature response of CSTR based ANN, MPC and MRAC

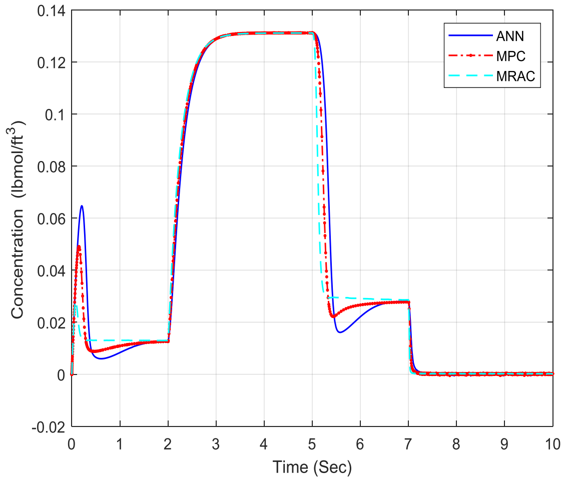


Figure 23. Tracking concentration response of CSTR based ANN, MPC and MRAC

Table 2. Comparison of performance between ANN, MPC and MRAC

Control type	***OS%***	***Ts (Sec)***	E_{ss}	***Cost function***	***Effect of noise***
ANN	24	1.5	0	25.5	High Effected
MPC	8	2.8	0	10.8	Medium Effected
MRAC	5	1.4	0	6.4	Low Effected

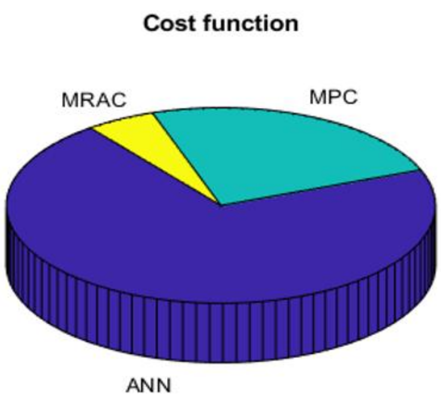


Figure 24: Cost function of ANN, MPC and MRAC

V. CONCLUSION

Various control strategies such as ANN, MPC, and MRAC were proposed and assessed using extensive simulations. The performance of the recommended controllers in terms of their characteristic time domain was assessed in the presence of undesirable situations. Based on the simulation findings, the three controllers were successfully designed. In terms of process functional minor adjustments, the results suggest that both proposed control approaches work well. The MRAC controller, according to the simulation results, is perfect since it has 0% steady-state error. The MRAC also maintains a steady performance in the presence of noise. Furthermore, the MRAC method gives more flexibility and precision in control action than the ANN and MPC strategies. In other words, the resiliency of the offered strategies in dealing with uncertainties during the tracking of the reference signal is taken into account.

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