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Multiple Neural Model Based Intelligent Adaptive Control for Shell and Tube Heat Exchanger Process

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Abstract: Model Reference Adaptive Control (MRAC) works on the principle of adjusting the controller parameters so that the output of the actual plant tracks the output of a reference model having the same reference input. Hence the success of the MRAC mainly depends on the best reference model. If the reference model is linear, the adaptive strategy cannot suit the control of nonlinear dynamic systems to extract the advantage of MRAC completely and hence the reference model is made to be multiple neural models in the proposed work. Multiple Neural models based Model Reference Adaptive Control (MN-MRAC) and modified Multiple Neural model based MRAC inbuilt with PD/ARX structure (MN-mMRAC-I and MN-mMRAC-II) are the three proposed controllers. The multiple neural models enhance the Model Reference Adaptive Control to handle all possible operating conditions of non-linear plant. The efficacy of proposed controllers is tested by extensive simulation studies on outlet temperature control of Shell and Tube Heat Exchanger (STHX) process.

Key words: Shell and Tube Heat Exchanger · Multiple Neural Model · Auto regressive with external estimator and Model Reference Adaptive Control

INTRODUCTION

Most of the industrial processes are nonlinear. Hence linear control strategy will not suit them, as there is shift in operating regions or parameter uncertainty situations. Here adaptive control techniques which provide a systematic approach for automatic adjustment of controllers dominated the field of process control. MRAC is a type of adaptive control.

The general idea behind Model Reference Adaptive Control is to create a closed loop controller with parameters that can be updated by comparing the desired response with the response from the reference model. Hence the reference model plays a vital role in MRAC. If the reference model is linear, then the system cannot handle change in operating conditions. To suit wide operating region, the reference model is a choice of multiple neural models in the proposed work.

Dougherty and Cooper [1] paved a good start to multiple model concept. They introduced a multiple model adaptive control for multivariable Dynamic Matrix Control (DMC). The method has combined the output of multiple linear DMC controllers and final input forwarded to the process is an interpolation of individual controller outputs, weighed based on the current value of the process variable.

In the work by J Prakash and K. Srinivasan the authors have represented the nonlinear system as a family of local linear statespace models. Several local PID controllers have been designed on the basis of respective linear models and nonlinear PID controller, whose output is the weighted sum of local PID controllers has been used to control the nonlinear process.

Vinodha *et al.* [2] attempted multiloop control of CSTR process via multiple model concept. The objective of this work is to design multiple model adaptive multiloop PID controllers each describing process dynamics at a specified level of operation.

Shell and tube Heat exchanger (STHX) is a widely used industrial process. Its process non-linearity and component added nonlinearity, gave a great challenge in control aspect. It has been observed in literature that hot water outlet temperature control of STHX is done by intelligent controllers , Model Predictive Control , Internal Model Control and Fuzzy Logic Control [3-5]. In the above said literature, the temperature control range is very

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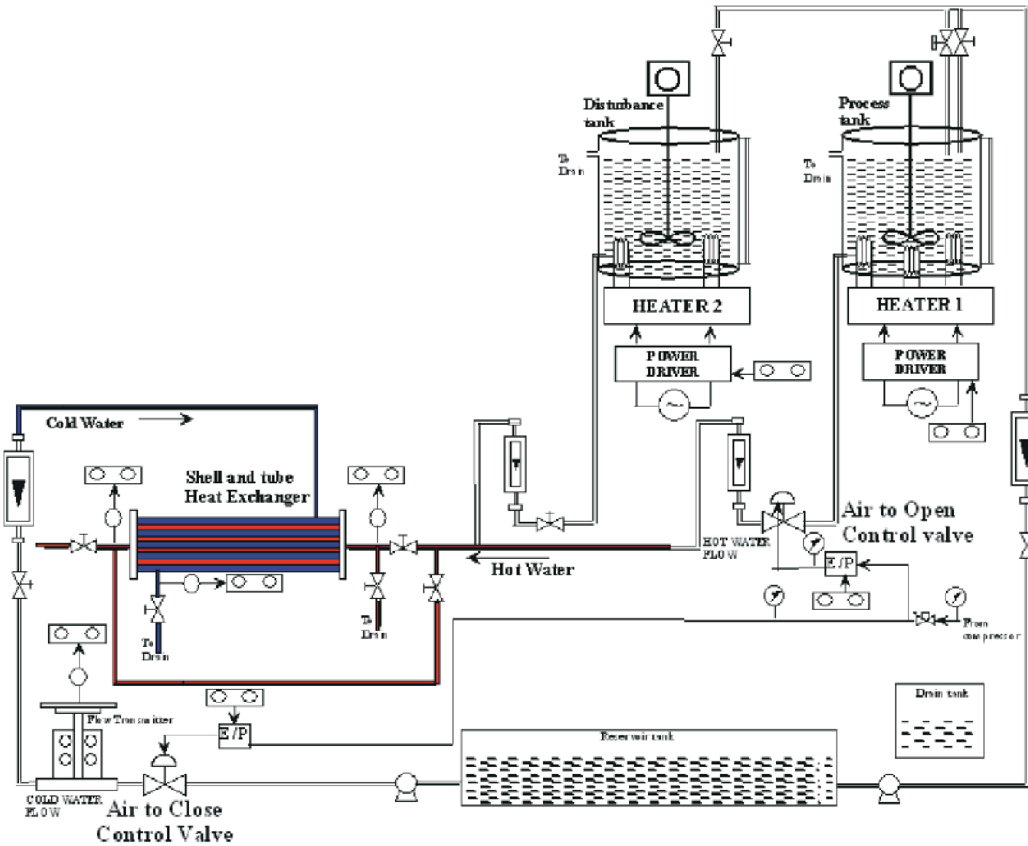

Fig. 1: Piping and Instrumentation diagram of Shell and Tube Heat Exchanger (STHX)

narrow and hence to extend the range, an attempt is made with Model Reference Adaptive Control by incorporating multiple neural models as a reference model. Neural models have been selected in a view to handle wider temperature range than a linear transfer function model.

The proposed controllers to control, outlet temperature of STHX process are Multiple Neural based MRAC (MN-MRAC) and modified type including PD and PD/ARX control in MRAC namely MN-mMRAC-I and MN-mMRAC-II.

Shell and Tube Heat Exchanger: A STHX [6] consists of a bundle of tubes enclosed within a cylindrical shell. One fluid flows through the tubes and second fluid flows within the space between the tubes and the shell. Heat is thus transferred from one fluid to the other through the tube walls, either from tube side to shell side or vice versa shown in Figure 1.

In this proposed work, water is taken as the medium for both shell and tube. The water is raised to a certain temperature in the process tank using thyristor drivers and this hot water is allowed to flow through the tubes where as shell carries the water in room temperature.

The hot and cold water inflow to the shell and tubes are manipulated using pneumatic control valves. RTD is used as temperature sensors at places of hot and cold water inlet and outlet. The hot water outlet temperature of tubes is the variable to be controlled, by manipulating the cold water flow to the shell. Differential Pressure Transmitter (DPT) is used for sensing the flow [7-15].

The direction of flow of hot and cold water decides the operation of STHX process to lie in co-current or counter current mode. If flow in shell and tubes are in same direction the mode is said to be co-current mode and counter current for opposite direction of flow as stated in Figure 2. The exchange of heat between shell and tube are shown in Figure 3 for co-current and counter current mode.

Energy Balance Equation: The energy balance for shell and tube [6] are given in equation (1) and (2) respectively with specification listed in Table 1.

Shell Side $\frac{\rho_s c_s v_s}{N} * \frac{dT_{co}}{dt} = \dot{m}_s c_s (T_{ci} - T_{co}) + \frac{h_s A_s}{N}(T_{ho} - T_{co})$ (1)

Tube Side $\frac{\rho_t c_t v_t}{N} * \frac{dT_{ho}}{dt} = \dot{m}_t c_t (T_{hi} - T_{ho}) + \frac{h_t A_t}{N}(T_{co} - T_{ho})$ (2)

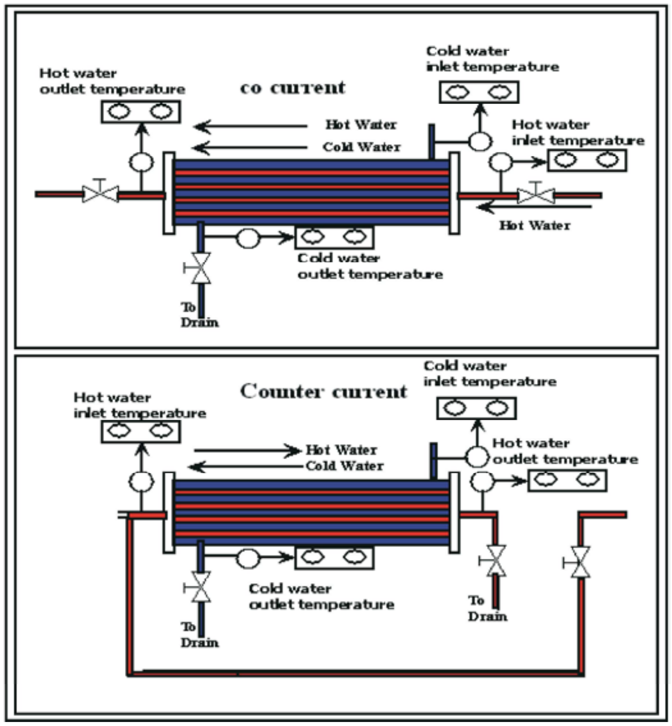

Fig. 2: Co-current and Counter current modes of STHX

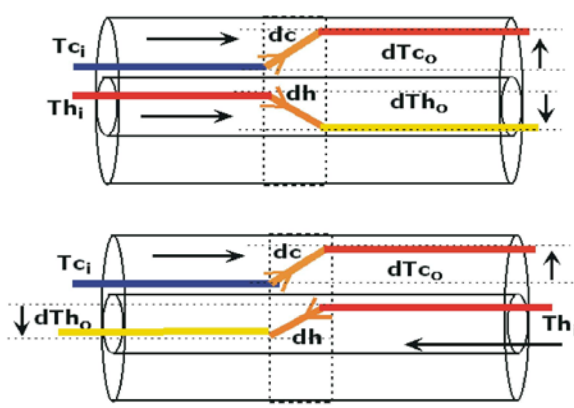

Fig. 3: Exchange of heat in co-current and counter current mode

Mutiple Neural Model Based Mrac Controller [MN-MRAC]: The proposed controller (MN-MRAC) uses multiple neural models facilitated by Model Reference Adaptive Control (MRAC) strategy. MRAC is a technique that works on adjustment of controller parameters θ_1 and θ_2 by adapting gain factors γ and $-\gamma$ using lyapunov rule, so that output of the plant tracks the reference model output. In the proposed work, the reference model is not a single model, but a choice of multiple models based on operating location of the process [6-15].

The block diagram of MN–MRAC controller for STHX process is shown in Figure 4.

Table 1: Parameter specifications of the STHX process at nominal operating point.

Inputs	Value	Units
Density of water (ρ_s, ρ_t)	1000	Kg/m^3
Specific Heat Capacity of water (C_s, C_t)	4230	J/kg °C
Shell Heat Transfer Area (A_s)	0.281	m^2
Tube Heat Transfer Area (A_t)	0.253	m^2
Shell side volume (V_s)	262 X 10	m^3
Tube side volume (V_t)	143 X 10	m^3
Heat transfer coefficient of Shell (h_t)	2162	$W/m^2°C$
Heat transfer coefficient of Tube (h_t)	2162	$W/m^2°C$
Mass flow rate of cold water ($\dot{m}_S$)	0 – 0.1222	Kg/s
Mass flow rate of hot water ($\dot{m}_t$)	0.0282	Kg/s
Cold water inlet temp (T_{ci})	33	°C
Hot water inlet temp (T_{hi})	55	°C
Number of control volume (N)	10	NA

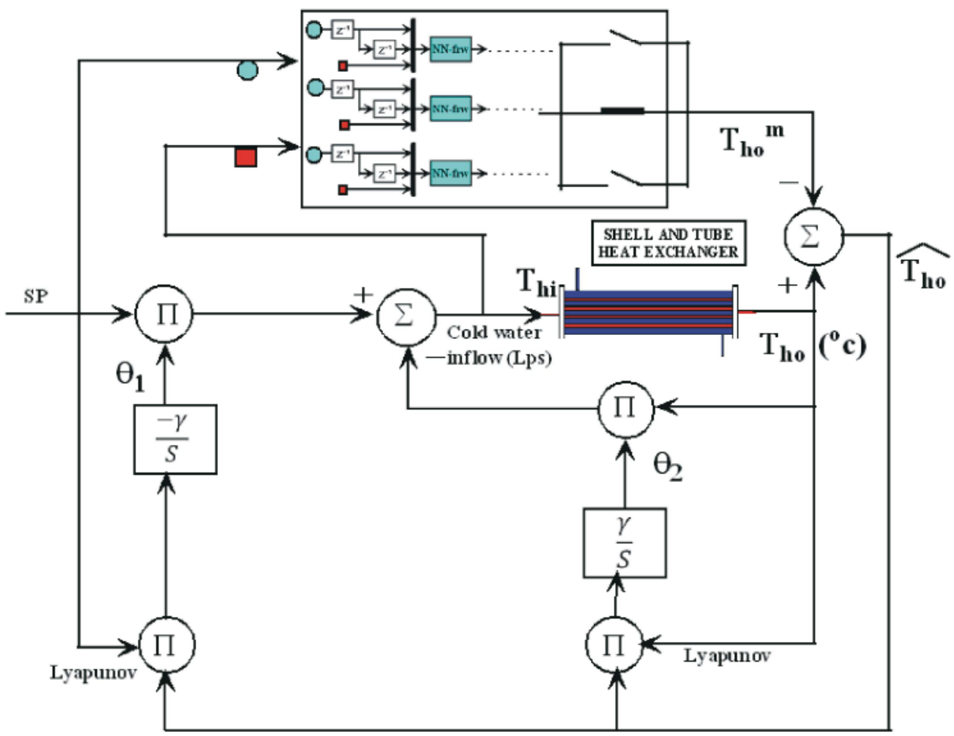

Fig. 4: Block diagram representation of MN-MRAC controller for STHX process

The control law to minimize error between the plant and model is,

$$\dot{m}_S(t) = \left\{ \begin{array}{l} \frac{d}{dT}\left(-\gamma\, sp(t)\, [T_{ho}(t) - T_{ho}{}^{m}(t)]\mathrm{sp}(t)\right) \\ -\frac{d}{dT}\left(-\gamma\, T_{ho}(t)\, [T_{ho}(t) - T_{ho}{}^{m}(t)]T_{ho}(t)\right) \end{array} \right\} \quad (3)$$

Plant equation: $T_{ho}(t) = STHX_{equ}(\dot{m}_S(t))$ (4)

Model equation: $T_{ho}{}^{m}(t) = NN\,\mathrm{mod}\,el(\dot{m}_S(t))$ (5)

Controller: $(\dot{m}_S(t) = \theta_1 sp(t) - \theta_2 T_{ho}(t)$ (6)

E = T_{ho} (t) – $T_{ho}{}^{m}$ (t) (7)

Artificial Neural Network (ANN): The modeling and control of non-linear systems [14] is not simple and is limited to restrictive classes of non-linear systems. The term "artificial neural network" originates from research which attempted to understand and proposed simple models with similar operation of the human brain. The Levenberg – Marquardt back propagation is the fastest algorithm utilized in modeling and control of non-linear systems. The neural architecture states.

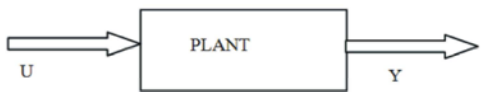

Fig. 5: Model identification of a process

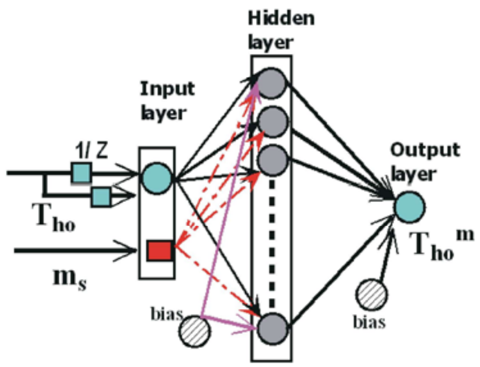

Fig. 6: Forward modeling of STHX process

Input Layer: Receive information from an external source and passes this information to the network

Hidden Layer: Receives information from the input layer and quietly does all information processing. The entire processing step is hidden from view.

Output Layer: Receives processed information from the network and sends the results out to an external receptor.

Neural Model Identification: Modelling meant some way to predict the output of a plant knowing the input. Hence the three components of interest are input, plant model and output as shown in Figure 5. If any two are known, it has a clear way to back calculate the third. The forward modeling of STHX process [refer Figure (6)] uses current input cold water inflow (m_s) and past outputs (delayed T_{ho}) to predict the current output T_{ho}^{m} as stated in equation (8).

$$T_{ho}^{m}(K+1) = f(T_{ho}(k), T_{ho}(k-1), m_s(k)) \quad (8)$$

Multiple Neural Models: The STHX process is a highly nonlinear process and hence single neural reference model will not satisfy the tracking criteria of actual plant at all operating ranges. Hence there is a need for multiple neural models.

The cold water inflow range of the STHX process is from 0.02 to 0.09 lps. The corresponding hot water outlet temperature is 43 to 47.5°C. To facilitate three neural models the cold water inflow (C_{if}) has been split into 3 regions as 0.02 to 0.06 lps, 0.04 to 0.08 lps and 0.06 to 0.09 lps.

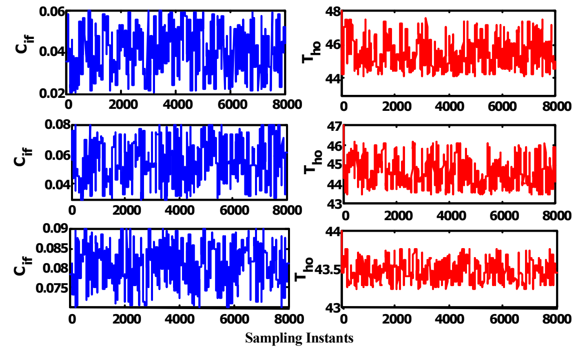

Fig. 7: Input and output training data

Table 2: NN-Forward model- Predefined Data

No of delayed inputs [C_{if}- Cold water inflow]	1
No of delayed outputs [T_{ho}- Hot water inflow]	2
Sampling interval	0.1 sec
Training algorithm	LM-BPN Algorithm
No of Hidden neurons	10
Learning rate	0.05
Objective function:	Mean Square Error (MSE) =1.268*e^{-006}
Activation function	Sigmoid, purelin

The input output training data for three regions are shown in Figure (7). The hot water outlet temperature for chosen three regions [refer Figure (8)] is found to be 44 – 47.5°C, 43.5-46 °C and 43.2 – 43.7°C. Based on the current setpoint, one of the three neural models act as the reference model. The updated manipulated variable acting as another input of reference model, helps to track the setpoint much faster. Table 2 describes the predefined data use to train the network [16-18].

Multiple Neural Model Based Modified Mrac [MN – mMRAC]: To improve the stability of the proposed MN-MRAC controller and to enhance its performance, two modifications have been suggested in the proposed work. The first modification [refer Figure (8)] includes PD action in the path of setpoint tracking. The respective control law is shown in equation (9).

$$\dot{m}_s(t) = \left\{ \begin{array}{l} \frac{d}{dT}\left(\begin{array}{c} -\gamma\, sp(t)\,[T_{ho}(t) - T_{ho}{}^{m}(t)] * sp(t) * \\ ([K_c(t) + K_i(t)] * e(t)) \end{array} \right) \\ -\frac{d}{dT}\left(-\gamma\, T_{ho}(t)\,[T_{ho}(t) - T_{ho}{}^{m}(t)] * T_{ho}(t)\right) \end{array} \right\} \quad (9)$$

The second modification includes ARX filter to eliminate the noise factors introduced by D action in PD tracking of setpoint [refer Figure (10)]. The respective control law is given in equation (10).

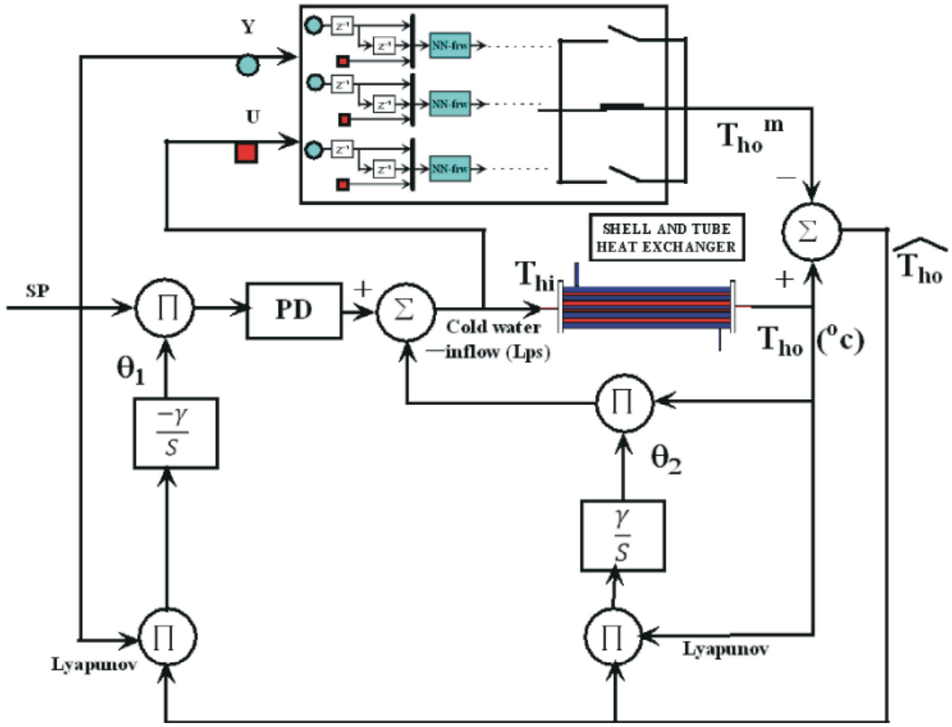

Fig. 8: Block diagram representation of MN-mMRAC-I Controller for STHX process.

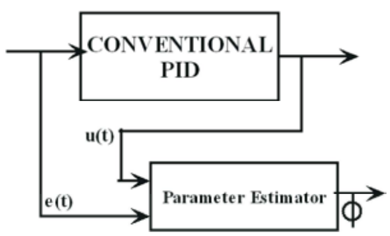

Fig. 9: ARX filter

$$\dot{m}_S(t) = \begin{Bmatrix} \frac{d}{dT}\begin{pmatrix} -\gamma\, sp(t)\,[T_{ho}(t) - T_{ho}{}^{m}(t)] * sp(t) * \\ J_{\min}([K_c(t) + K_i(t)] * e(t) \text{ or } (\emptyset) * e(t)) \end{pmatrix} \\ -\frac{d}{dT}\left(-\gamma\, T_{ho}(t)\,[T_{ho}(t) - T_{ho}{}^{m}(t)] * T_{ho}(t)\right) \end{Bmatrix} \tag{10}$$

MN-mMRAC-II is a control strategy that brings minimum derivative output using ARX filter, where the estimator is designed as state transfer model to predict the controller output. The design parameter $\varnothing$ of ARX filter is calculated using Least Square Estimation (LSE) by collecting input output data as shown in Figure 9. The related equation of LSE are given in equations (11), (12) and (13).

$$\hat{u}(t) = \varphi^{T}(t)\emptyset \tag{11}$$

$$\begin{bmatrix} u_1 \\ \vdots \\ \vdots \\ \vdots \\ u_n \end{bmatrix} = \begin{bmatrix} \varphi_{1,1} & \cdots & \varphi_{1,n} \\ \vdots & \cdots & \vdots \\ \vdots & \cdots & \vdots \\ \vdots & \cdots & \vdots \\ \varphi_{m,1} & \cdots & \varphi_{m,n} \end{bmatrix} * \begin{bmatrix} \emptyset_1 \\ \vdots \\ \vdots \\ \vdots \\ \emptyset_n \end{bmatrix} \tag{12}$$

$$\varnothing = [\varphi^{T} \varphi]^{-1} \varphi^{T} u \tag{13}$$

To support smooth control transition, MN-mMRAC-II supports two modes of operation; namely PD and ARX modes. To achieve bumpless control the transfer between these modes is done by switching based on a certain threshold value [19].

Servo Response: The servo response of proposed controllers (MN-MRAC, MN-mMRAC-I and MN-mMRAC-II) is shown in Figure 11 with respective manipulated cold water inflow. The wide variation in set temperature from 43 to 47.5 °C has been better tracked by all the three proposed controllers, with superior performance seen in MN-mMRAC-II. Table 3 gives the performance measure of proposed controllers for servo response. Among the three controllers MN-mMRAC eliminates offset completely with minimum overshoot, setting time, ISE and IAE values.

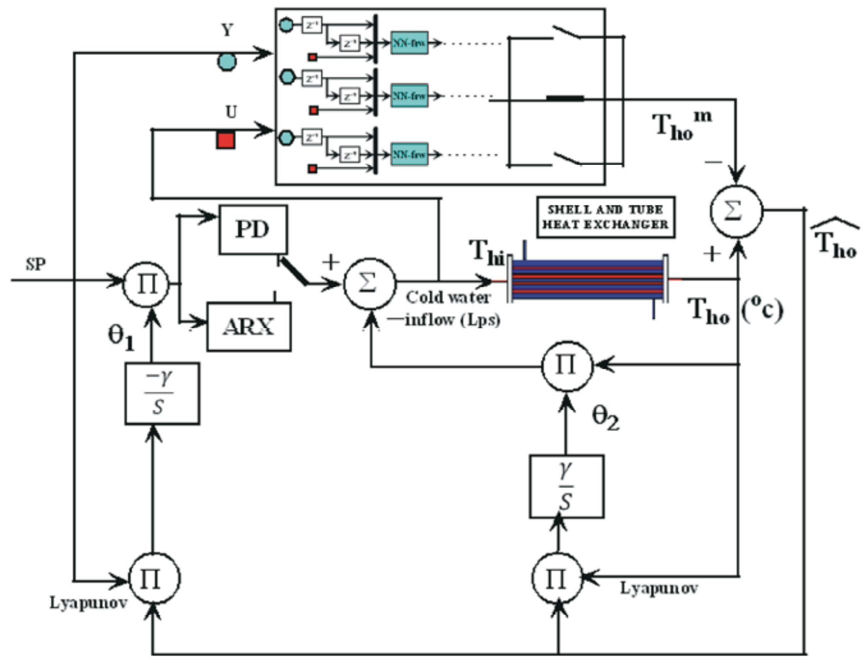

Fig. 10: Block diagram representation for MN-mMRAC-II Controller for STHX process

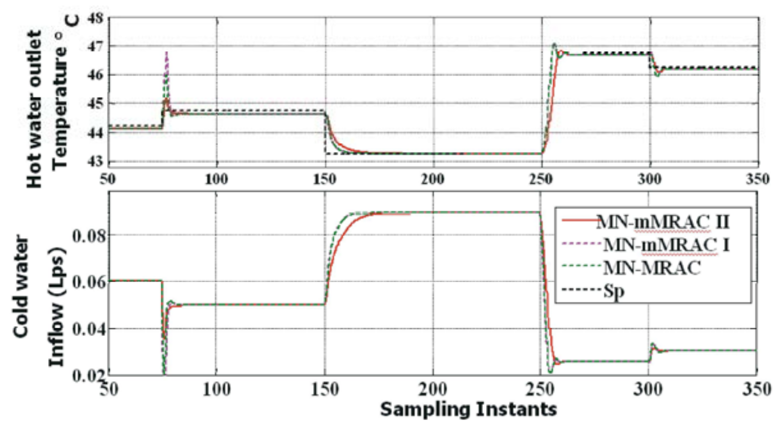

Fig. 11 Servo responses of proposed controllers

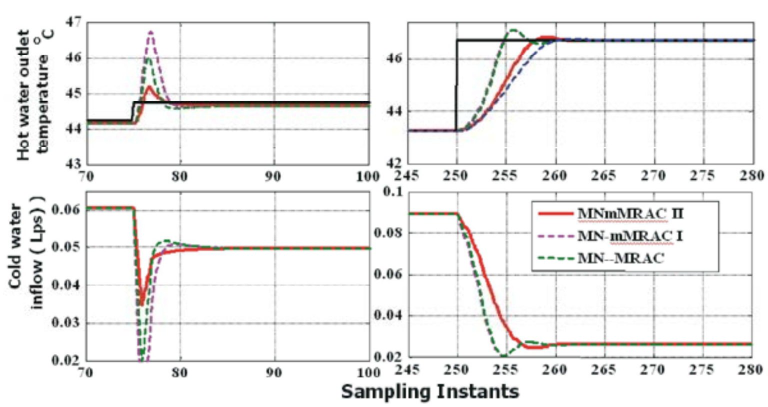

Fig. 12: Servo responses of proposed controllers showing clear vision between 70 to 100 and 245 to 280 samples

Table 3: Performance indices for servo response of proposed controllers

Sampling Instants		75 to 149	150to 249	250 to 299	300to 349
MN-MRAC	%Mp	0.7	0	0	0.08
	Offset	0.1	0	0	0.08
	ts	82	165	265	311
	ISE	25	43	320	6
	IAE	95	59	134	39
MNmMRAC-I	%Mp	0.9	0	0.5	0.7
	Offset	0.1	0	0	0.08
	ts	84	165	265	310
	ISE	57	41	306	7
	IAE	110	58	130	39
MNmMRAC-II	%Mp	0.96	0	0.5	0.3
	Offset	0	0	0	0
	ts	80	174	262	309
	ISE	11	30	296	6
	IAE	80	46	128	38

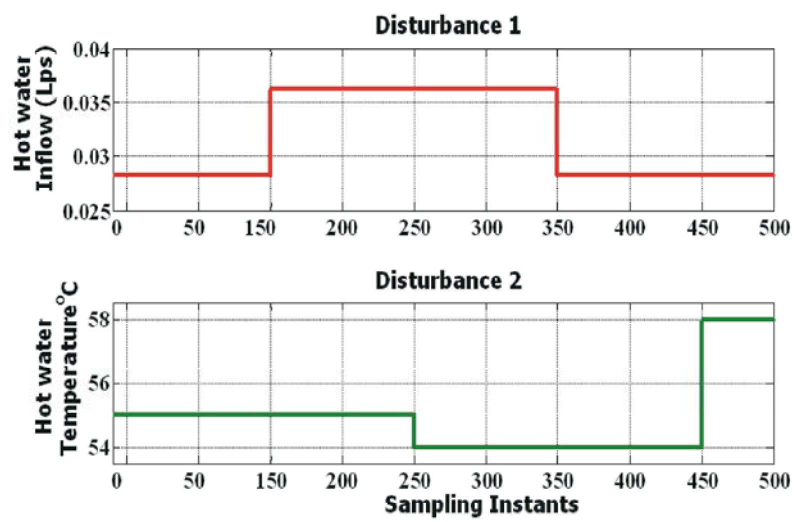

Fig. 13: Hot Water Inflow (m_t) and Temperature disturbance (T_{hi})

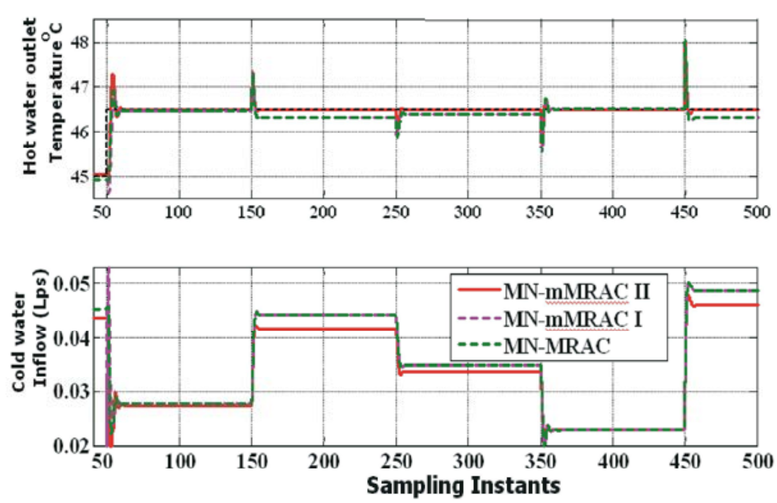

Fig. 14: Servo-Regulatory response of proposed Controllers

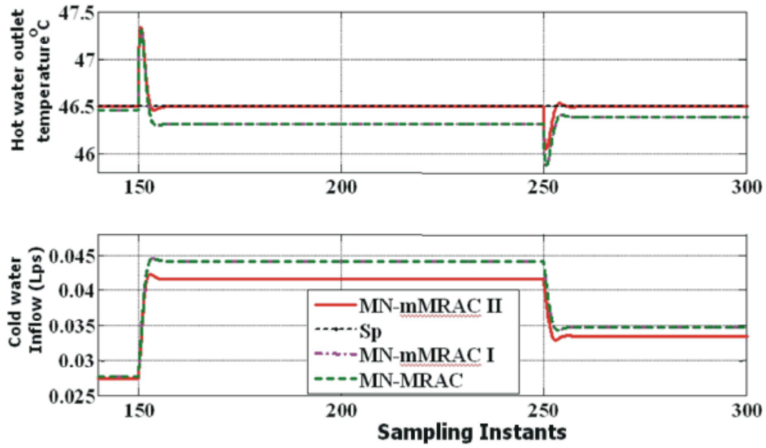

Fig. 15: Servo-Regulatory response showing clear vision between 150 to 300 samples

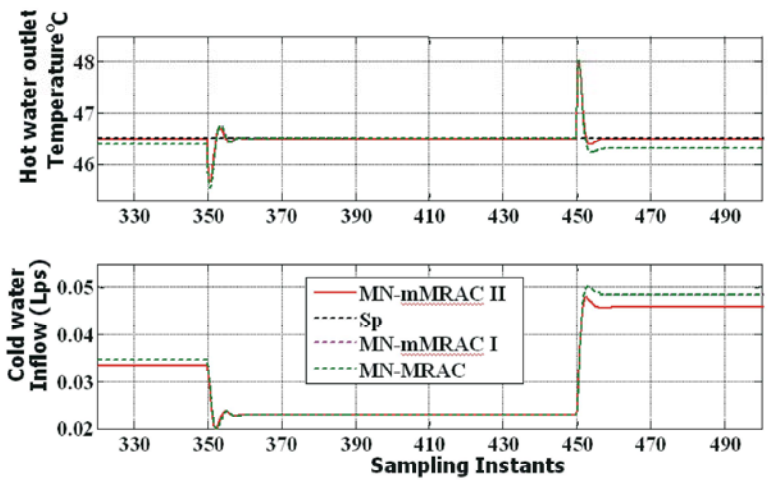

Fig. 16: Servo-regulatory response showing clear vision between 330 to 490 samples

Table 4: Performance indices for servo-regulatory response of proposed controller

Sampling Instants		149 to 249	249 to 349	349 to 449	449 to 500
MN-MRAC	%Mp	0.41	0.2	0.53	0.5
	offset	0.18	0.1	0	0.2
	ts	307	410	507	607
	ISE	24	29	19	45
	IAE	120	154	77	117
MNmMRAC-I	%Mp	0.41	0.2	0.53	0.5
	offset	0.18	0.1	0	0.2
	ts	307	407	507	607
	ISE	24	29	19	45
	IAE	120	157	77	117
MNmMRAC-II	%Mp	0.08	0.04	0.49	0.2
	offset	0	0	0	0
	ts	307	409	507	607
	ISE	8	3	9	26
	IAE	21	16	24	32

A clear enlarged vision of servo response has been shown Figure 13 for sampling instants between 70 to 100 and 245 to 280.

Servo Regulatory Response: The hot water outlet temperature is disturbed by change in the hot water inlet temperature (T_{hi}) and inlet hot water flow rate (m_t). To obtain the servo- regulatory responsesthe disturbance pattern utilized is shown in Figure 14. The flow rate has been increased to 0.0362 kg/s from its nominal value of 0.0282 kg/s at 150th sec and maintained till 350th sample. Similarly the hot water inlet temperature (T_{hi}) is decreased to 54°C at 250th sample and maintained till 450th sample. Then it has been raised to 58°C [refer Figure (13)].

The concerned servo-regulatory response is shown in Figure 14, with manipulated variable change. Among the three proposed controllers, MN-mMRAC-II is found to be better in servo-regulatory tracking. A clear enlarged vision of servo-regulatory response is shown in Figure 15 and Figure 16 respectively for sampling instants between 150 to 300 and 330 to 500. The performance indices of the proposed controllers are listed out in Table 4.

CONCLUSION

In this paper an attempt has been made to control the nonlinear STHX with attractive reference model selection of Model Reference Adaptive Controller. The proposed controllers have been proved to be effective in controlling the outlet temperature of STHX process. The results obtained from simulated differential equation model of STHX reveal that proposed controllers are good in responding servo-regulatory inputs.

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