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A New Design Methodology of Self Tuning Control Algorithm for an Interacting MIMO Process

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Abstract: The problem of controlling the liquid level and flow rate in the presence of nonlinearity and disturbance justifies the need for developing adaptive control schemes. This paper focuses on developing Indirect Adaptive Control(IAC) strategies for an interacting liquid level Multi Input Multi Output(MIMO) process, which is predominant in most of process industries. A mathematical model that comprises of four discrete transfer functions for each of the operating regions is obtained. These models are estimated using Recursive Least Square Estimation algorithm(RLSE). Self Tuning Controllers(STC) which is a class of IAC are designed and implemented through simulation on the model of the chosen process.

Key words: Coupled tank process · Multi Input Multi Output system · Recursive Least Square Estimation · Self Tuned Adaptive control · Minimum Degree Pole Placement

INTRODUCTION

With the increased dependency on computers to control industrial processes and also with the recent trends in technology, process automation has been gaining widespread appreciation in almost all process industries. These industries involve liquid at some point or the other for its production process. So it is highly essential for accurate liquid level measurement and control at a desired level in most process industries. In order to improve upon the quality of any product and to achieve better plant operation there is a need for development of perfect controllers. To achieve an effective controller design an accurate modeling of the process is very much needed.

System Identification involves building mathematical models of dynamic system based on a set of measured data [1]. The Recursive Least Squares (RLS) algorithm is one of the most popular identification technique which estimates the process in an efficient recursive manner. Due to unforeseen reasons, parameters in the processes get changed significantly. Consequently, a general control system is to provide efficient control of the processes inspite of these parameter changes. The control of dynamic system in the presence of large uncertainties and constraints are of great interest for many applications. In such case, the controller has to take the appropriate control action. Digital control is becoming increasingly important as most of the recent advanced controllers are implemented through digital devices.

Plant Identification and performance monitoring of control loops are done by manipulating the discrete data. In general, for digital control, it is convenient to use discrete time models [2].

I.D. Landau implemented a two degrees of freedom Pole placement controller using R, S and T polynomials for a hot Dip galvanizing process [3]. A. Cuencaa *et al*. proposed the methodology for the design and tuning of RST digital controllers that includes a brief description about the pole placement approach [4, 5]. Hajer Gharsallaoui *et al*. compared well-known conventional RST polynomial control and a recent approach of a RST controller design based on the property of flatness for a Thermal Process [6]. Andrea Pintea *et al*. described a method of RST controller algorithm for a system with unstable zero. Also a comparative analysis is given for IMC and RST control algorithms by applying these controllers on a variable speed wind turbine [7].

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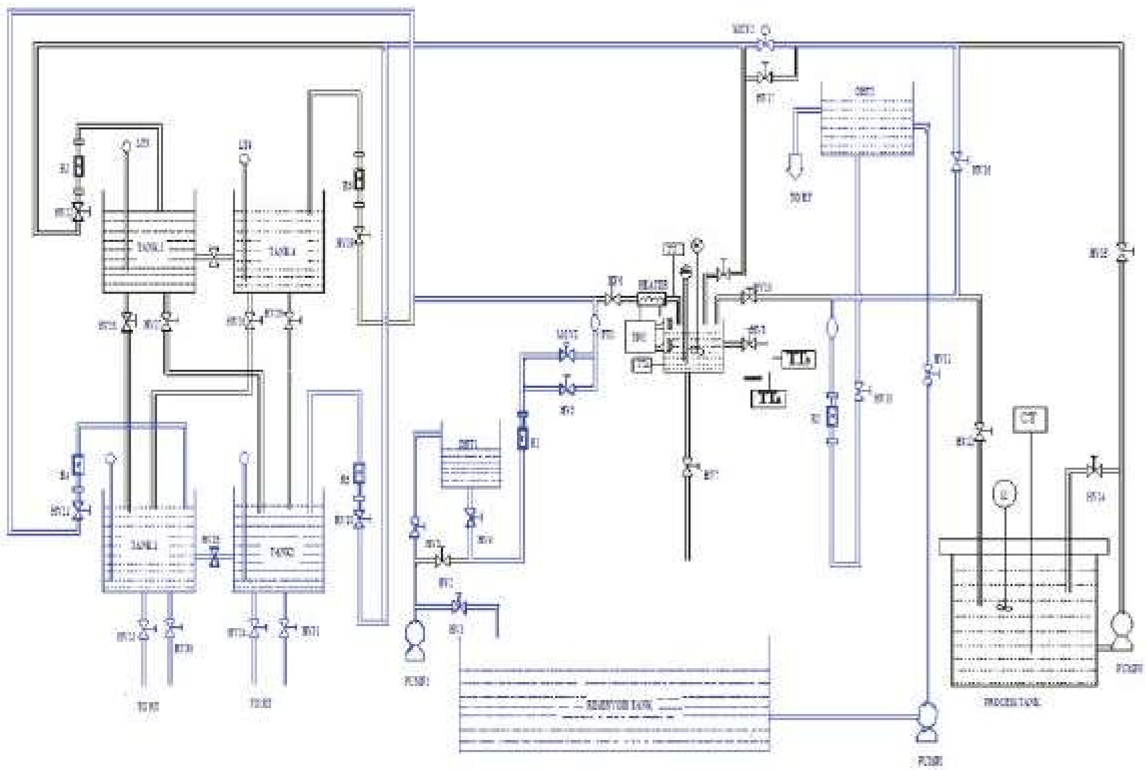

Fig. 1: The Piping and Instrumentation diagram of the laboratory interacting coupled tank setup

In this paper, the laboratory interacting coupled tank system is chosen and it is complex due to the interactions between the multiple variables existing in the system. As the coupled tank process has varying system dynamics, it is a difficult task to exercise control of level in both the tanks.

Hence Adaptive Controllers find suitability in this situation. This work compares the qualitative and quantitative performances of the Self Tuned controller based on Pole Assignment Approach and Self Tuned RST controller using Minimum Degree Pole Placement(MDPP) approach.

Interacting Coupled Tank Process: The Piping and Instrumentation diagram of the laboratory interacting coupled tank process setup is shown in Fig. 1. The pilot process consists of two cylindrical tanks (Tank1 and Tank2) interconnected by a flow channel which results in the interaction between levels of the two tanks. Water gets discharged from reservoir to Tank1 and Tank2. Rotameters (R1 and R2) are used to measure the inflow rates to the tanks, which are manipulated using Motorized Control Valves (MCV1 and MCV2). The capacitance type level transmitters are used to sense the levels in the tanks. Data Acquisition Card(DAQ) receives input from these transmitters. The motorized control valves are actuated by the control signal which originates from the DAQ card.

Mass Balance Equation: The schematic diagram of the chosen Interacting coupled tank system is illustrated in Fig. 2. Eqns. (1) and (2) represents the mass balance equations for tank1 and tank2. The rate of change of liquid volume in each tank is equal to the net flow of liquid into the tank. The volumetric inflow rate into the tank1 and tank2 are q_{in1} and q_{in2}. The volumetric flow rate from the tank1 and tank2 are q_{01} and q_{02}. Flow rate between tank1 and tank2 is q_{12}. The height of the liquid level is h_1 in tank1 and h_2 in tank2.

The mass balance equations of tank1 and tank 2 are given in Eqns. (1) and (2).

$$A_1 \frac{dh_1}{dt} = q_{in1} - q_{o1} - q_{12} \tag{1}$$

$$A_2 \frac{dh_2}{dt} = q_{in2} - q_{o2} + q_{12} \tag{2}$$

The system model can be formulated by ordinary differential equation using Bernoulli's law as shown in Eqns. (3) and (4).

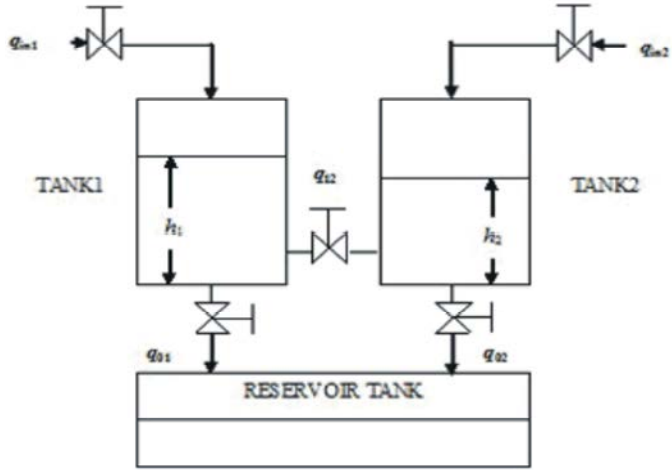

Fig. 2: Schematic diagram of coupled tank process

$$\frac{dh_1}{dt} = \frac{q_{in1}}{A_1} - \frac{c_d a_1}{A_1}\sqrt{2gh_1} - \frac{c_d a_{12}}{A_1}\sqrt{2g(h_1 - h_2)} \quad (3)$$

$$\frac{dh_2}{dt} = \frac{q_{in2}}{A_2} - \frac{c_d\ a_2}{A_2}\sqrt{2gh_2} + \frac{c_d a_{12}}{A_1}\sqrt{2g(h_1 - h_2)} \quad (4)$$

The cross sectional area of tank1 and tank2 are A_1=A_2=1130.4cm^2, The restriction areas in the outlet pipes of tank1 and tank2 are a_1=a_2=3.9cm^2. Restriction area of interconnecting pipe is a_{12}=1.27cm^2 . The co-efficient of discharge c_d is 0.8 and g is the acceleration due to gravity. The maximum capacity of two tanks is 25cm. To design the control systems for this process the equations are linearized by considering small variations in q_{in1}, q_{in2}, h_1 and h_2. The variations are measured with respect to nominal operating conditions. The hand valves are adjusted so that the levels in both the tanks are brought to nominal condition initially. Nominal values of q_{in1}, q_{in2} are 26 and 20.75 l/hr and for h_1 and h_2 are 12.5 and 12.1cm respectively.

Multi-Loop Process: The four models relating the two controlled outputs h_1 and h_2 with two manipulated inputs q_{in1} and q_{in2} are essential to design the multi-loop controllers [8]. The model transfer functions with the flow rates as manipulated inputs and the levels as controlled outputs are as follows:

$$G_{11}(s) = \left(\frac{h_1}{q_{in1}}\right)_{q_{in2}} \quad ; \quad G_{21}(s) = \left(\frac{h_2}{q_{in1}}\right)_{q_{in2}}$$

$$G_{12}(s) = \left(\frac{h_1}{q_{in2}}\right)_{q_{in1}} \quad ; \quad G_{22}(s) = \left(\frac{h_2}{q_{in2}}\right)_{q_{in1}}$$

Fig. 3(a) shows the open loop response of the processes G_{11} and G_{21} under three different operating regions. The process is initially maintained at nominal operating condition (h_1=12.6cm, h_2=12.1cm). In 800th sampling instant 5LPH change is given in q_{in1}. This causes h_1 to change from 12.6 to 16.02cm.

Due to interaction h_2 has reached the steady state value of 14.3cm from its nominal value. In 1800th sampling instant 5LPH change is given in q_{in1}. This causes h_1 to change from 16 to 20cm. Due to interaction h_2 has reached the steady state value of 16.5cm from 14.3cm. In 2800th sampling instant 5LPH change is given in q_{in1}. T his causes h_1 to change from 20 to 24.5cm. Due to interaction h_2 has reached the steady state value of 18.8 cm from 16.5cm. Fig. 3(b) displays the change in q_{in1} keeping q_{in2} in nominal operating condition.

The open loop response for the processes G_{12} and G_{22} under three operating regions are shown in Fig. 4(a). In the same manner, step change is given in q_{in2}, maintaining q_{in1} in nominal condition. Fig. 4(b) displays the change in q_{in2} with q_{in1} in nominal condition.

System Identification: A Posteriori approach attempts to model the system without making assumptions about its structure. This approach is referred to as black-box modeling, since the resulting model is simply a "black box" whose behavior mimics that of the system. This class of models describes the relationship between the system inputs and outputs, but may provide little structural or functional information about the system or its components [4].

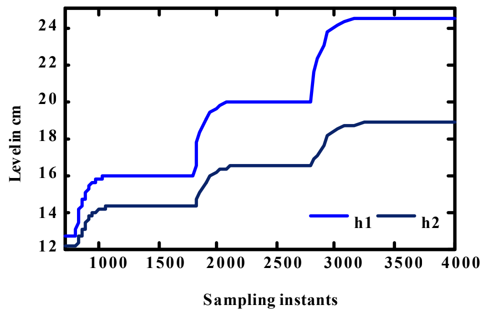

Fig. 3(a): Open loop response for G_{11} and G_{21} (change in q_{in1})

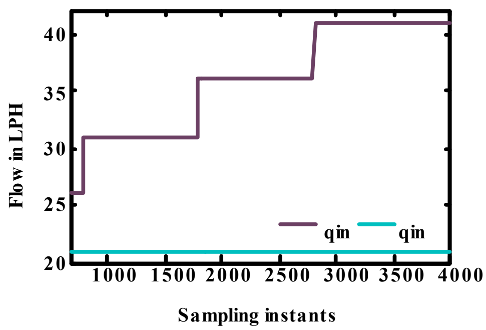

Fig. 3(b): Change in inflow rate (q_{in1})

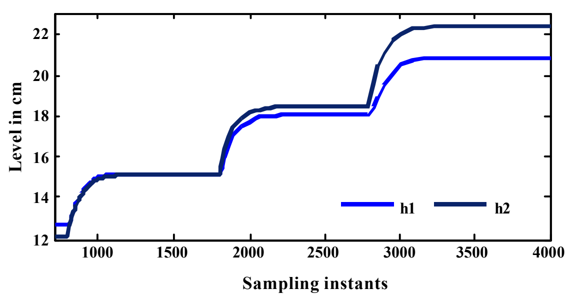

Fig. 4(a): Open loop response for G_{12} and G_{22} (change in q_{in2})

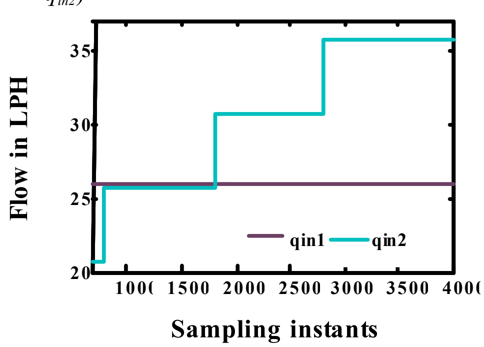

Fig. 4(b): Change in inflowrate (q_{in2})

The input-output or transfer function model in the discrete time domain is called a pulse transfer function and is given by.

$$H_d(z) = \frac{B(z)}{A(z)}$$

where A and B are polynomials in z and are given below.

$$A(z) = z^n + a_1 z^{n-1} + ... + a_{n-1} z^{n-(n-1)} + a_n$$

$$B(z) = b_{m-1} z^m + ... + b_m$$

Based on the apriori knowledge, the laboratory level process has Numerator and Denominator degrees as 2 with the general transfer function form as.

$$H_d(z) = \frac{b_1 z + b_2}{z^2 + a_1 z + a_2}$$

Recursive Least Square Estimation (RLSE): Recursive parameter estimation methods are online identification procedures that continuously and recursively update the parameters of a process model. The input to the process, $u(k)$ is also concurrently channeled to a model that tries to emulate the dynamics of the process.

Based on the given input, the adjustable predictor predicts the output of the process. The predicted output is compared with the actual output of the process. The prediction error, $\varepsilon(k)$ is then used by the Parameter Adaptation Algorithm (PAA) to update the model parameters so that it can more closely represent the process dynamics [2].

The general equation of recursive least square estimation is presented in the Equ. (5) as follows:

$$\begin{bmatrix} \text{Current Parameter} \\ \text{Estimate, } \hat{\theta}(k) \end{bmatrix} = \begin{bmatrix} \text{Previous Parameter} \\ \text{Estimate, } \hat{\theta}(k-1) \end{bmatrix} + \begin{pmatrix} \text{Correction} \\ \text{factor} \end{pmatrix} * \left[\begin{pmatrix} \text{New} \\ \text{Observation} \end{pmatrix} - \begin{pmatrix} \text{Prediction with} \\ \text{old estimate} \end{pmatrix} \right] \quad (5)$$

Equ.(5) is rearranged to the recursive version of Least Square Estimation(LSE) method where the current parameter estimate vector $\hat{\theta}(k)$ is updated in each step based on Parameter Adaptation Algorithm.

$$\hat{\theta}(k) = \hat{\theta}(k-1) + \frac{P(k)\phi(k)}{I + \phi^T(k)P(k-1)\phi(k)}(y(k) - \hat{\theta}^T(k-1)\varphi(k)) \quad (6)$$

where $\phi(k)$ is the Measurement/Observation vector, $P(k)$ is the covariance matrix and is given in Equ. (7).

Table 1: Discrete Transfer function Models obtained from RLSE algorithm

Operating region (OR)	Tank 1 (q_{in2} constant) Δq_{in1} (LPH)	Δh_1 (cm)	Δh_2 (cm)	Tank 2 (q_{in1} constant) Δq_{in2} (LPH)	Δh_1 (cm)	Δh_2 (cm)	Discrete Process Transfer Function obtained from RLSE method $H_d(z)$
OR1	26-31	12.60-16.02	12.10-14.30	20.75-25.75	12.6-15.0	12.1-15.1	$\begin{bmatrix} \frac{0.0008117z+0.0007695}{z^2-1.849z+0.8518} & \frac{0.00372z+0.002952}{z^2-1.485z+0.4987} \\ \frac{0.0002106z+0.0002038}{z^2-1.905z+0.9061} & \frac{0.0009313z+0.0008664}{z^2-1.802z+0.8052} \end{bmatrix}$
OR2	31-36	16.02-20.00	14.30-16.50	25.75-30.75	15.0-18.0	15.1-18.4	$\begin{bmatrix} \frac{0.0009945z+0.0009262}{z^2-1.805z+0.8079} & \frac{0.000481z+0.0004627}{z^2-1.888z+0.8899} \\ \frac{0.0001889z+0.0001834}{z^2-1.915z+0.9154} & \frac{0.0005237z+0.0004989}{z^2-1.863z+0.8646} \end{bmatrix}$
OR3	36-41	20.00- 24.50	16.50-18.80	30.75-35.75	18.0-20.8	18.4-22.4	$\begin{bmatrix} \frac{0.002348z+0.002089}{z^2-1.699z+0.7041} & \frac{0.0002999z+0.000289}{z^2-1.894z+0.8948} \\ \frac{0.001803z+0.001697}{z^2-1.825z+0.8325} & \frac{0.003025z+0.002546}{z^2-1.589z+0.5958} \end{bmatrix}$

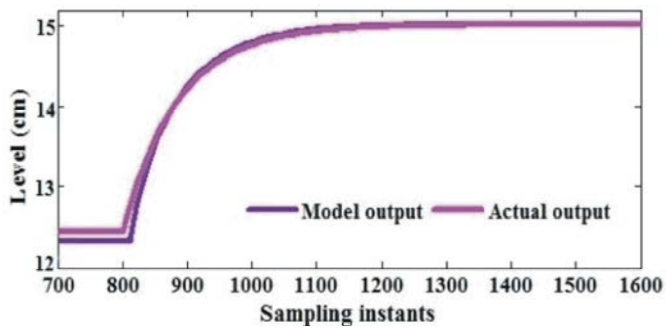

Fig. 5(a): Time domain validation for the model G_{11}

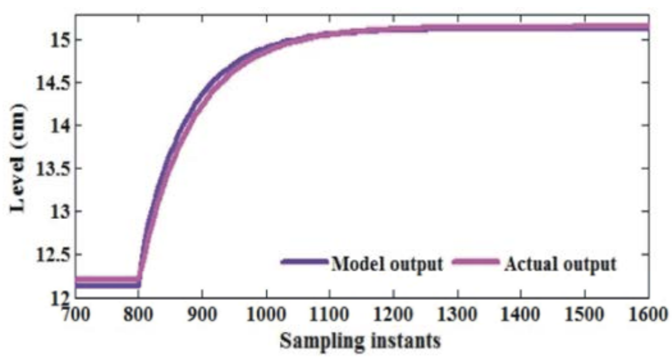

Fig. 5(b): Time domain validation for the model G_{22}

The discrete process transfer function obtained from RLSE method are tabulated in Table 1.

$$P(k) = P(k-1) - [P(k-1)\phi(k)\phi^T(k)P(k-1)]A^{-1} \qquad (7)$$

where, $A = \{I + \phi^T(k)P(k-1)\phi(k)\}$

Model Validation: It is an important step in model building and is accomplished by matching output from white box approach (Actual output) with discrete transfer function model. Fig. 5(a) and 5(b) shows the validation for the models G_{11} and G_{22} respectively for OR1.

Self Tuning Controller: The block diagram of a Self Tuning Controller (STC) is shown in Fig. 6. The block labeled "*Estimation*" represents an online estimation of the model parameters using RLSE algorithm. The estimator is responsible for estimating the plant parameters during every sampling instant. It uses past inputs and outputs of the plant as well as present output. The appropriate controller parameters are then derived from the estimated values.

The block labeled "*Controller Design*" represents an online solution to a design problem for a system with known parameters or with estimated parameters [9]. The block labeled "*Controller*" is to calculate the control action with the controller parameters computed by its preceding block. Here, h_1ref and h_2ref are reference inputs to controller1 and controller2 respectively. The h_1 and h_2 are the corresponding levels of tank1 and tank2. The system can be viewed as an automation of process modeling/estimation and design, in which the process model and the control design are updated at each sampling interval.

In this paper, two different STCs are designed and implemented for the Interacting Coupled Tank Process. In the first method, pole assignment approach is implemented. In the second approach, RST controller is designed and implemented using Minimum Degree Pole Placement(MDPP) approach.

Self Tuned Pole Placement Controller(STC-PP): The STC-PP controller is based on the assignment of poles in a closed feedback control loop and it is designed to stabilize the closed loop while the characteristic polynomial should have previously determined poles. Apart from the stability requirement, good pole configuration can make it relatively easy to obtain desired closed loop response [10, 11].

Transfer function of the controlled system is;

$$H(z) = \frac{b_1 z + b2}{z^2 + a_1 z + a_2}$$

Control law is given Equ.(8).

$$u_k = q_0 e_k + q_1 e_{k-1} + q_2 e_{k-2} + (1-\gamma)u_{k-1} + \gamma u_{k-2} \tag{8}$$

where e_k is error ($e_k = h_{ref}(k) - h(k)$) and controller parameters q_0, q_1, q_2 and γ are calculated by solving following Diophantine equation.

$$A(z)P(z) + B(z)Q(z) = D(z)$$

Here, The initial parameter estimates are $\hat{a}_1, \hat{a}_2, \hat{b}_0 \hat{b}_1$.

The polynomials $A(z)$ and $B(z)$ are as follows,

$$A(z) = z^2 + \hat{a}_1 z + \hat{a}_2$$
$$B(z) = \hat{b}_1 z + \hat{b}_2$$
$$P(z) = z^2 - z(1+\gamma) - \gamma$$
$$Q(z) = q_0 z^2 + q_1 z + q_2$$
$$D(z) = z^2 + d_1 z + d_2$$

In which,

$$d_1 = -2\exp(-\xi\omega T_0)\cos\left(\omega T_0\sqrt{1-\xi^2}\right) \qquad \text{for } \xi \le 1$$
$$d_1 = -2\exp(-\xi\omega T_0)\cosh\left(\omega T_0\sqrt{\xi^2-1}\right) \qquad \text{for } \xi > 1$$
$$d_2 = \exp\left(-2\xi\omega T_0\right)$$

The desired closed loop response is achieved by proper selection of the reference model. Based on the apriori knowledge, the reference model considered in this work is of 2nd order whose characteristic equation is given in Equ. (9).

$$s^2 + 2.\xi.\omega.s + \omega^2 \tag{9}$$

To have stable closed loop poles, the damping factor ξ>0 and natural frequency ω>0. The sampling period, T_0 should be less than the dominant time constant of the system. Wittenmark and Astrom [12] recommend that the value for natural frequency should lie in the range $0.45 \le \omega * T_0 \le 0.90$ for stable closed loop poles.

Solving the Diophantine equation leads to following relations for controller parameters.

$$\gamma = q_2 \frac{\hat{b}_2}{\hat{a}_2} \quad ; \quad q_2 = \frac{s_1}{r_1}$$
$$q_1 = \frac{\hat{a}_2}{\hat{b}_2} - q_2\left(\frac{\hat{b}_1}{\hat{b}_2} - \frac{\hat{a}_1}{\hat{a}_2} + 1\right)$$
$$q_0 = \frac{1}{\hat{b}_1}(d_1 + 1 - \hat{a}_1 - \gamma)$$

where,

$$r_1 = \left(\hat{b}_1 + \hat{b}_2\right)\left(\hat{a}_1\hat{b}_1\hat{b}_2 - \hat{a}_2\hat{b}_1^2\right)$$
$$s_1 = \hat{a}_2\left[\left(\hat{b}_1 + \hat{b}_2\right)\left(\hat{a}_1\hat{b}_2 - \hat{a}_2\hat{b}_1\right) - \hat{b}_2\left(\hat{b}_1 d_2 - \hat{b}_2 d_1 - \hat{b}_2\right)\right]$$

Estimation of Model Parameters Using RLSE Algorithm: The model taken up for the process is;

$$H(z) = \frac{b_1 z + b_2}{z^2 + a_1 z + a_2}$$

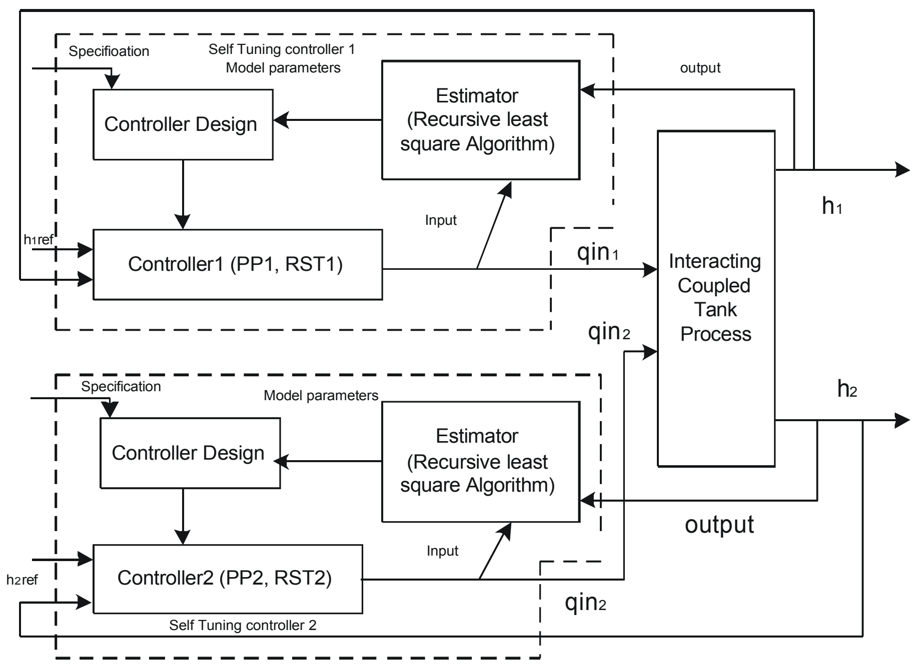

Fig. 6: Block diagram of Multi-loop Self Tuning Control system

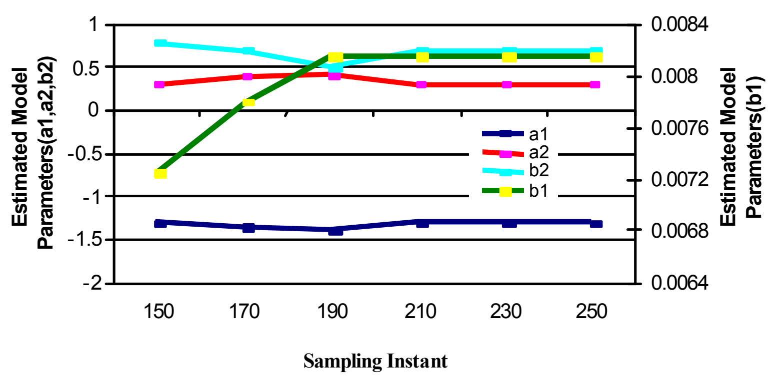

Fig. 7(a): Estimated model parameters using RLSE method

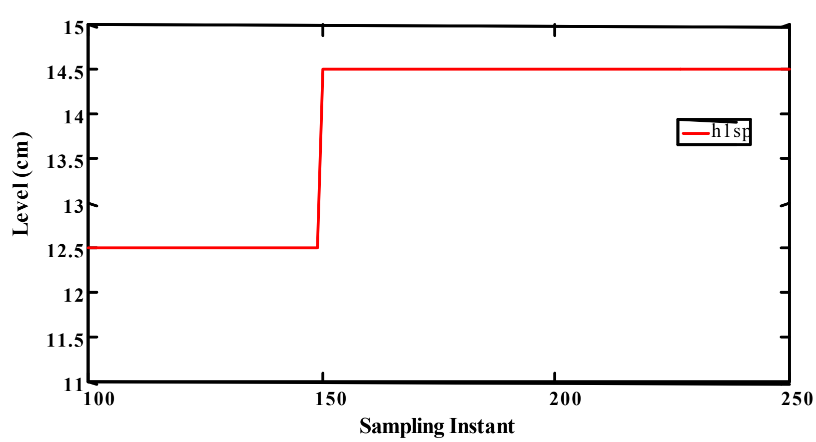

Fig. 7(b): Change in setpoint(h_{1sp})

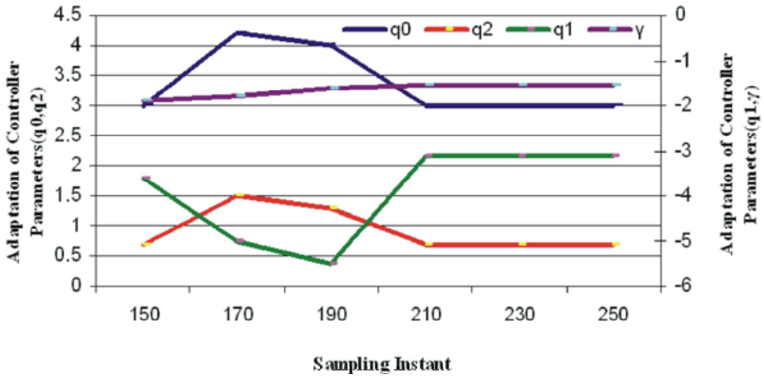

Fig. 8: Adaptation of controller parameters(STC-PP)

Table 2: Adapted controller parameters

	Adapted Controller Parameters			
Sampling Instant	q_0	q_1	q_2	γ
150th	3	-3.6	0.6786	-1.9
170th	4.22	-5	1.5	-1.8
190th	4	-5.5	1.3	-1.6
210th	2.999	-3.118	0.6786	-1.548
230th	2.999	-3.118	0.6786	-1.548
250th	2.999	-3.118	0.6786	-1.548

The estimated model parameters a_1, a_2, b_1 and b_2 for change in h_{1sp} (set point of h_1) during sampling instant (150^{th} -250^{th}) are shown in Fig. 7(a).

For a sudden change in h_{1sp} (set point of h_1) of 2cm applied at 150^{th} sampling instant as shown in Fig. 7(b), the change in the model parameters a_1, a_2, b_1 and b_2 are estimated using RLSE method (Fig. 7(a)). For the given set point change in h_1, from 150^{th} -250^{th} sampling instant, the variation in a_1, a_2, b_1 and b_2 are from -1.4 to -1.305, 0.3 to 0.3093, 0.00725 to 0.008161 and 0.8 to 0.7054 respectively.

Adaptation of controller parameters: The adaptation of controller parameters q_0, q_1, q_2 and γ for change in h_{1sp} during sampling instant(150^{th} -250^{th}) are shown in Fig. 8.

The adapted controller parameters q_0, q_1, q_2 and γ during sampling instant (150^{th}-250^{th}) are tabulated in Table 2.

Self Tuned RST Controller (STC-RST): The digital controller design methods are combined with the system model identification techniques. A rigorous, high performance digital control design relating to multi input multi output control in the presence of deterministic disturbances is designed and implemented. The methodology of the RST controller is applicable only to plants that can be modeled by a continuous time system characterized by a transfer function of maximum degree equal to 2, without or with time delay. The plants must also have a time delay less than one sampling period.

The transfer function of the controlled system is;

$$H(z) = \frac{B(z)}{A(z)} = \frac{b_0 z + b_1}{z^2 + a_1 z + a_2}$$

Based on the compatibility condition [9], the desired closed loop reference model must have the same zeros as the plant. Hence the transfer function of the reference model is selected as presented below.

$$H_m(z) = \frac{B_m(z)}{A_m(z)} = \frac{b_{m0} z + b_{m1}}{z^2 + a_{m1} z + a_{m2}}$$

The discrete closed loop transfer operator is;

$$H_m(z) = \beta \frac{b_0 z + b_1}{z^2 + a_{m1} z + a_{m2}} = \frac{b_{m0} z + b_{m1}}{z^2 + a_{m1} z + a_{m2}}$$

where $b_{m0} = \beta b_0$ and

$$\beta = \frac{1 + a_{m1} + a_{m2}}{b_0 + b_1}$$

which gives unit steady state gain.

The RST controller equation is given by;

$$Ru(k) = T^{*} h_{ref}(k) - S^{*} h(k)$$

The closed loop characteristic polynomial (Diophantine Equation) is;

$$AR + BS = Ac = A_0 A_m$$

In the design of STC-RST, no process zeros are cancelled, Hence,

$$B^{+} = 1$$

$$B^{-} = B = b_0 z + b_1$$

The Diophantine equation becomes;

$$(z^2 + a_1 z + a_2)(z + r_1) + (b_0 z + b_1)(s_0 z + s_1) = (z^2 + a_{m1} z + a_{m2})(z + a_0)$$

Replacing $z = -b_1/b_0$ and solving for r_1 results in;

$$r_1 = \frac{a_0 a_{m2} b_0^2 + (a_2 - a_{m2} - a_0 a_{m1}) b_0 b_1 + (a_0 + a_{m1} - a_1) b_1^2}{b_1^2 - a_1 b_0 b_1 + a_2 b_0^2}$$

Equating coefficients of terms z^2 and z in Diophantine equation results in;

$$s_0 = \frac{b_1(a_0 a_{m1} - a_2 - a_{m1} a_1 + a_1^2 + a_{m2} - a_1 a_0)}{b_1^2 - a_1 b_0 b_1 + a_2 b_0^2} + \frac{b_0(a_{m1} a_2 - a_1 a_2 - a_0 a_{m2} + a_0 a_2)}{b_1^2 - a_1 b_0 b_1 + a_2 b_0^2}$$

$$s_1 = \frac{b_1(a_1 a_2 - a_{m1} a_2 + a_0 a_{m2} - a_0 a_2}{b_1^2 - a_1 b_0 b_1 + a_2 b_0^2} + \frac{b_0(a_2 a_{m2} - a_2^2 - a_0 a_{m2} a_1 + a_0 a_2 a_{m1})}{b_1^2 - a_1 b_0 b_1 + a_2 b_0^2}$$

and $T(q) = \beta A_0(z) = \beta(z + a_0)$

The value of a_0 is taken as unity.

Adaptation of controller parameters: The adaptation of controller parameters for r_1, s_0, s_1 and T for change in h_{1sp} during sampling instant(150th -250th) are shown in Fig. 9.

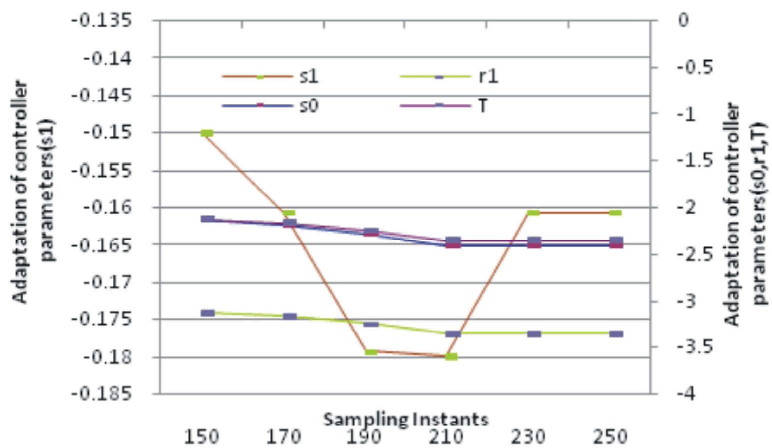

Fig. 9: Adaptation of controller parameters(STC-RST)

The adapted controller parameters r_1, s_0, s_1 and T during sampling instant (150th-250th) are tabulated (Table 3).

Table 3: Adapted controller parameters

	Adapted Controller Parameters			
Sampling Instant	r_1	s_0	s_1	T
150th	-3.123	-2.128	-0.15	-2.123
170th	-3.156	-2.176	-0.1607	-2.158
190th	-3.247	-2.274	-0.1794	-2.247
210th	-3.354	-2.405	-0.18	-2.354
230th	-3.354	-2.405	-0.1607	-2.354
250th	-3.354	-2.405	-0.1607	-2.354

RESULTS AND DISCUSSION

Fig. 10 shows the closed loop servo response of tank1 and tank2 with STC-PP and STC-RST controllers. Initially h_1 and h_2 are allowed to settle in the nominal condition (h_1=12.6cm and h_2=12.1cm). The setpoint change of 2cm for h_1 is applied at 150th and again a servo change of 1cm is applied at 250th sampling instant. Due to interaction between the tanks there is a considerable rise in h_2 The designed controllers are able to track the setpoint changes. The setpoint change for h_2 is applied at 300th, 340th and 400th sampling instances. As a result h_1 also increases and returns to its set point due to the action of controllers.

Responses of STC-PP Controllers: The estimated model parameters a_1, a_2, b_1 and b_2 for change in setpoint (h_{1sp}) at various sampling instants are shown in Fig. 11(a).

The controller1 parameters are then self tuned for the variation in model parameters and implemented in the control loop1. The adaptation of controller1 parameters q_0, q_1, q_2 and γ for change in h_{1sp} at various sampling instants are shown in Fig.11(b).

Fig. 11(c) shows the corresponding responses of STC-PP controller for the setpoint changes in h_1 and h_2. At 150th and 250th sampling instant, the controller1 increases the qin_1 inorder to increase the level h_1 to the setpoint change. Simultaneously, the controller2 decreases qin_2 to bring back the level h_2 to the nominal condition. At 300th, 340th and 400th sampling instances, the controller2 increases the qin_2 to increase the level h_2 to an increase in setpoint. Simultaneously, the controller1 decreases qin_1 to bring back the level h_1 to the setpoint.

Responses of STC-RST Controllers: The estimated model parameters b_0, b_1 , a_1 and a_2 for change in setpoint(h_{1sp}) for various sampling instants are shown in Fig. 12(a). Based on the estimated model parameters the controller1 parameters are then self tuned and implemented in the control loops. The coefficients of R, S and T polynomials for change in h_{1sp} at various sampling instants are shown in Fig. 12(b).

Fig. 12(c) shows the corresponding responses of STC-RST controller for the setpoint changes in h_1 and h_2. The controllers take necessary action to vary the inflow rate to tank1 and tank2 in order to track the setpoint changes. Similar to Figures from 11(a) to 11(c) and from 12(a) to 12(c), the controllers STC-PP and STC-RST have their variations inorder to bring the h_2 closer to the given setpoint in loop1.

Table 4 presents the performance indices of self tuning controllers for servo changes implemented in the interacting coupled tank system under study. From Table 4, ISE values for change in h_1 of tank1 corresponding to STC-PP are reduced to 10% compared to STC-RST. The IAE values for change in h_2 of tank2 corresponding to STC-PP are reduced to 4% compared to STC-RST. While applying servo changes, it is observed that the STC-PP possess faster settling time when compared to that of STC-RST.

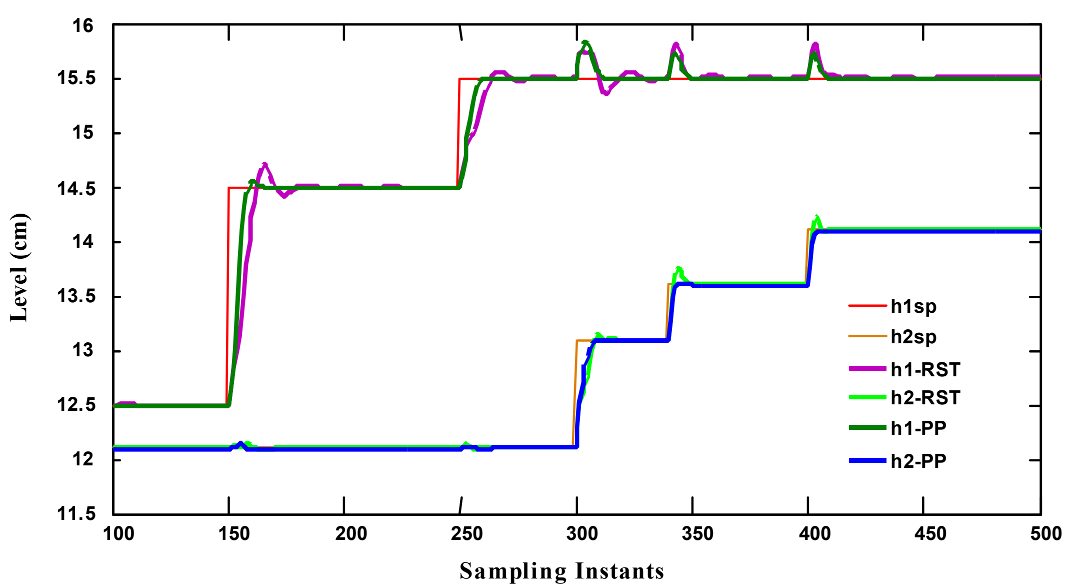

Fig. 10: Closed loop Servo Tracking response of tank1 and tank2 with STC-PP and STC-RST controllers

Table 4: Comparison of Performance Indices

		Tank1			Tank2	
Parameters	Controller	150-250	250-300	300-340	340-400	400-500
Settling Time(Sec)	STC-PP	20	12	13	6	7
	STC-RST	54	40	28	14	14
Integral Square Error (ISE)	STC-PP	1510	1758	1322	1452	1589
	STC-RST	1661	1947	1407	1539	1686
Integral Absolute Error (IAE)	STC-PP	150.5	156.9	133.3	140.8	148.5
	STC-RST	153.5	160.9	136.5	145	154.2

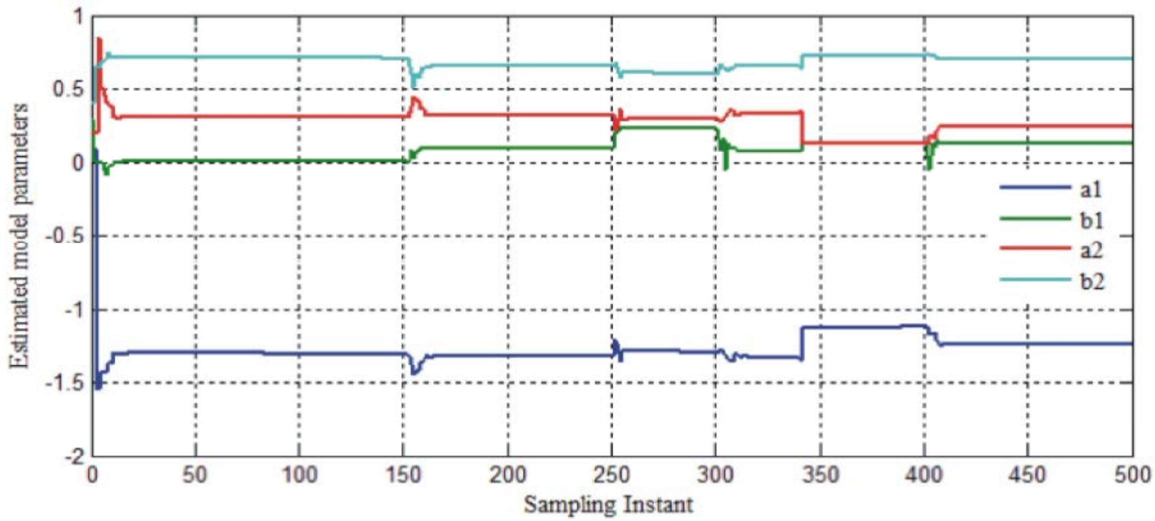

Fig. 11(a): Estimated model parameters(RLSE) with STC-PP in the control loop1

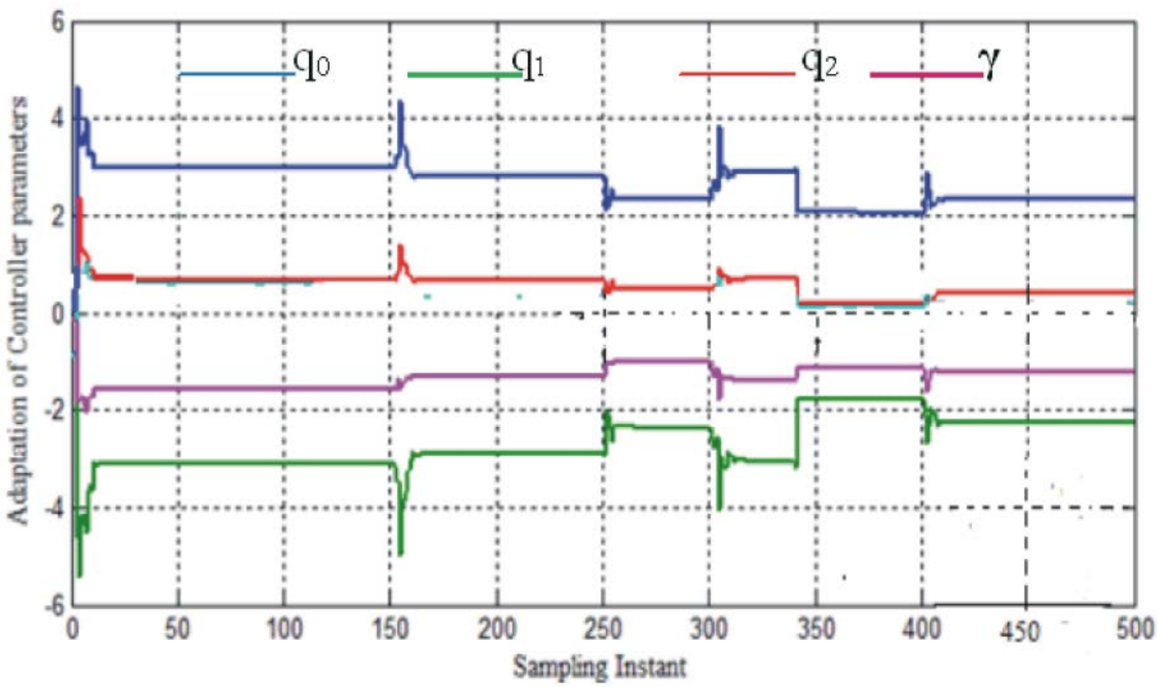

Fig. 11(b): Adaptation of controller1 parameters (STC-PP)

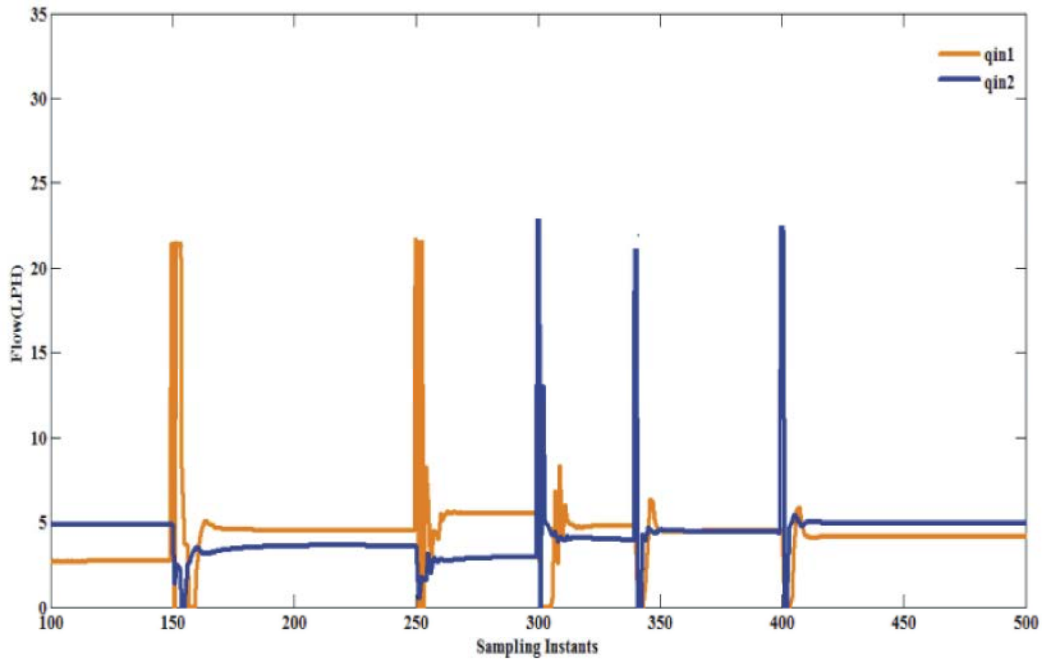

Fig. 11(c): Responses of STC-PP controllers

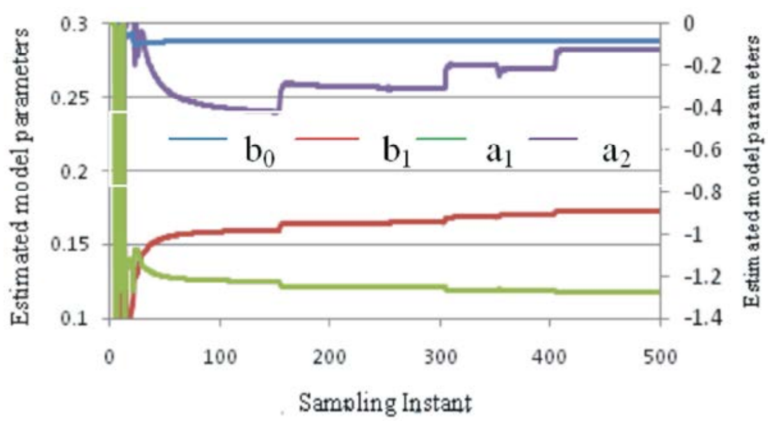

Fig. 12(a): Estimated model parameters(RLSE) with STC-RST in the control loop1

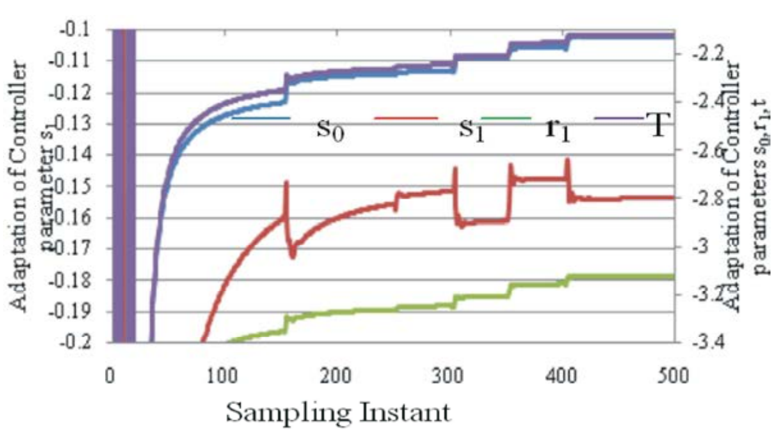

Fig. 12(b): Adaptation of controller1 parameters (STC- RST)

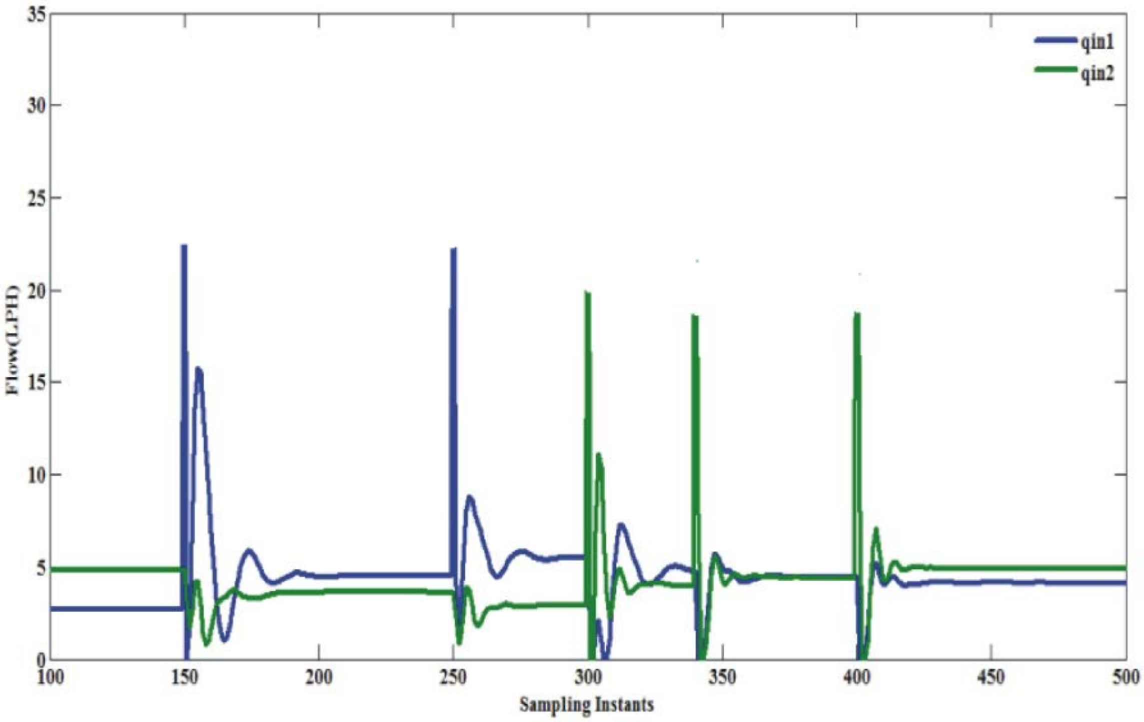

Fig. 12(c): Responses of STC-RST controllers

CONCLUSION

This paper has dealt with the design and implementation of Indirect Adaptive Self tuning controllers using Pole Placement Technique and RST polynomials. These controllers are designed using the models obtained from the Recursive Least Square Estimator. The Self tuned Pole Placement Controller has yielded a satisfactory performance without much overshoot upon implementation on the Interacting Coupled tank process. As there are many number of parameters to be determined, the computational complexity is more. Interaction effects are also considered in order to achieve better servo tracking. It can be concluded that the proposed Self Tuning Controllers based on Pole placement approach outperforms well for the chosen coupled tank interacting process.

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