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DESIGN OF OPTIMIZED PI CONTROLLER WITH IDEAL DECOUPLER FOR A NON LINEAR MULTIVARIABLE SYSTEM USING PARTICLE SWARM OPTIMIZATION TECHNIQUE

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Abstract. *Most of the industrial processes are multivariable in nature. The Multi Input Multi Output (MIMO) process has the difficulty in controller design because of changes in process dynamics and interactions between process variables. The quadruple tank process is a novel laboratory equipment which has been used in control literature to illustrate many concepts in MIMO systems. The objective of the current study presented in this paper is to design an optimized PI controller for quadruple tank process with decoupler using particle swarm optimization and to compare it with Model Reference Adaptive Control (MRAC) technique. The validity and robustness of the proposed system is tested using simulation results. A good performance of set point tracking and disturbance attenuation is obtained for the decoupled process.*
Keywords: Multivariable control, Decoupler, PI controller, Quadruple tank process, Relative gain array, Model reference adaptive control, Particle swarm optimization

1. **Introduction.** The majority of the industrial processes are nonlinear and multivariable systems. There are always complicated interactions existing between the measurement signals and control signals. Because of the interactions between several input and output variables, it is difficult to design a suitable controller for MIMO systems. To handle multivariable systems, several control techniques are available as given in [1]. Multivariable control problems are traditionally solved by centralized PID controllers to obtain the desired overall control function. Centralized controller design for MIMO systems suffers from potential problems associated with complex computations, maintenance due to the size and a high risk of failure even though it provides a better performance as in [2,3]. In turn decentralized strategies based on mathematical analysis, provide flexible and scalable solutions with simple single input single output (SISO) controllers.

This paper presents a design methodology for auto tuned decentralized PI controller using decoupling and Particle swarm optimization to solve the problem of interactions in quadruple tank process, which is a bench mark multivariable process used in control literature. The quadruple tank process is a novel multivariable laboratory process that consists of four interconnected water tanks. It has been used to illustrate both traditional and advanced multivariable control strategies and can be utilized as an educational tool in describing advanced multivariable control techniques. The results are compared with MRAC technique, which is one of the traditional adaptive control techniques.

Quadruple tank process provides interesting challenges in the multivariable control design because it can be configured in two different operating points known as minimum phase condition and non minimum phase condition. i.e., one of its two multivariable zeros can be placed either in left half of s-plane [minimum phase condition] or right half of s-plane [non minimum phase condition].

In this paper a controller design methodology is proposed for the multivariable process in both minimum phase and non minimum phase operating points wherein the control system is designed in three steps: First, a decoupler is designed to split the MIMO system into two single input single output (SISO) control loops; Then, a decentralized control structure is configured using Relative Gain Array (RGA) concept: Finally, the best PI controller parameters are tuned by optimization using PSO and the results are compared.

The concepts behind this study are organized as follows. Section 2 gives the description of quadruple tank process and the linearised mathematical modelling of the system. The design of decoupler is presented in Section 3 and Relative Gain Array concepts for selecting input/output pairing are explained in Section 4. Section 5 explains the design of MRAC technique. Section 6 describes the Particle Swarm Optimization for optimizing the PI controller parameters, which is followed by results and discussions in Section 7. The conclusions are given in Section 8.

2. **Process Description and Modelling.** A quadruple tank apparatus which was proposed in [4] has been used in chemical engineering laboratories to illustrate the performance limitations for multivariable systems posed by ill-conditioning, right half plane transmission zeros and model uncertainties.

The quadruple tank system consists of four interconnected tanks and two pumps. The schematic of the quadruple tank equipment is presented in Figure 1.

The process inputs are v_1 and v_2 (input voltages to the pumps), and the outputs are y_1 and y_2 (voltages from level measurement devices). The target is to control the level of the lower two tanks by manipulating inlet flow rates. The output of each pump is split into two by using a three-way valve. Thus, each pump output goes to two tanks, one lower and another upper, diagonally opposite and the ratio of the split up is controlled by the position of the three way valves. With the change in position of the two valves, the

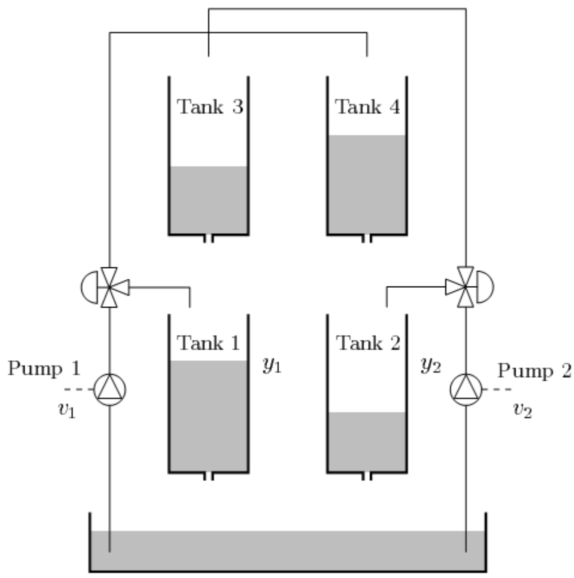


FIGURE 1. Schematic of quadruple tank system

system can be appropriately placed either in the minimum phase or in the non-minimum phase.

Let the parameter γ be determined by how the valves are set. If γ_1 is the ratio of flow to the first tank, then $(1-\gamma_1)$ will be the flow to the fourth tank. Similarly if γ_2 is the ratio of flow to the second tank, then $(1-\gamma_2)$ will be the flow to the third tank. The voltage applied to pump 'i' is V_i and the corresponding flow rate is K_iV_i. The parameters $\gamma_1, \gamma_2 \in (0,1)$ are determined from how the valves are set prior to an experiment. The flow to tank '1' is $\gamma_1 K_c V_1$ and the flow to tank '4' is $(1-\gamma_1)K_cV_1$ and similarly for Tank '2' and Tank '3'. The acceleration of gravity is denoted as 'g'. The measured level signals are $y_1 = k_c h_1$ and $y_2 = k_c h_2$ [4].

The non linear state equations of the four tank system are given in Equations (1)-(4).

$$\frac{dh_1}{dt} = -\frac{a_1}{A_1}\sqrt{2gh_1} + \frac{a_3}{A_1}\sqrt{2gh_3} + \frac{\gamma_1 k_c}{A_1}v_1 \tag{1}$$

$$\frac{dh_2}{dt} = -\frac{a_2}{A_2}\sqrt{2gh_2} + \frac{a_4}{A_2}\sqrt{2gh_4} + \frac{\gamma_2 k_c}{A_2}v_2 \tag{2}$$

$$\frac{dh_3}{dt} = -\frac{a_3}{A_3}\sqrt{2gh_3} + \frac{(1-\gamma_2)k_c}{A_3}v_2 \tag{3}$$

$$\frac{dh_4}{dt} = -\frac{a_4}{A_4}\sqrt{2gh_4} + \frac{(1-\gamma_1)k_c}{A_4}v_1 \tag{4}$$

where

A_i is cross sectional area of Tank 'i'

a_i is cross section of outlet hole of Tank 'i'

h_i is water level in Tank 'i'.

The levels of the four tanks (h_i) are considered as the state variables (x_i), the voltages applied to pumps (v_1 and v_2) are the input variables (u_i) and the levels of tank '1' and tank '2' are the output variables (y_i).

For linearizing the non linear system, $x_i = h_i - h_i^0$ and $u_i = v_i - v_i^0$ where h_i^0 and v_i^0 are the steady state values of h_i and v_i respectively.

The linearized state space model with system matrices is obtained by using Tailor series expansion which is given in Equation (5) and the model is given in Equation (6)

$$\dot{x}_l = \dot{h}_l \approx f(h_i^0, v_i^0) + \frac{\partial f(h,v)}{\partial h^T}\bigg|_{h_i=h_i^0}(h_i - h_i^0) + \frac{\partial f(h,v)}{\partial v^T}\bigg|_{v_i=v_i^0}(v_i - v_i^0) \tag{5}$$

in which $f(h_i^0, v_i^0) \xrightarrow{\text{yields}} 0$; $\frac{\partial f(h,v)}{\partial h^T}|_{h_i=h_i^0} \xrightarrow{\text{yields}} A$; $\frac{\partial f(h,v)}{\partial h^T}|_{h=h_i^0} \xrightarrow{\text{yields}} X$; $\frac{\partial f(h,v)}{\partial v^T}|_{v_i=v_i^0} \xrightarrow{\text{yields}} B$ and $(v_i - v_i^0) \xrightarrow{\text{yields}} U$.

The linearized state model is given by

$$\begin{aligned} \dot{X} &= AX + BU \\ Y &= CX + DU \end{aligned} \tag{6}$$

where $A = \begin{bmatrix} -\frac{1}{T_1} & 0 & \frac{A_3}{A_1T_3} & 0 \\ 0 & -\frac{1}{T_2} & 0 & \frac{A_4}{A_2T_4} \\ 0 & 0 & -\frac{1}{T_3} & 0 \\ 0 & 0 & 0 & -\frac{1}{T_4} \end{bmatrix}$; $B = \begin{bmatrix} \frac{\gamma_1 k_1}{A_1} & 0 \\ 0 & \frac{\gamma_2 k_2}{A_2} \\ 0 & \frac{(1-\gamma_2)k_2}{A_3} \\ \frac{(1-\gamma_1)k_1}{A_4} & 0 \end{bmatrix}$; $C = \begin{bmatrix} k_c & 0 & 0 & 0 \\ 0 & k_c & 0 & 0 \end{bmatrix}$

and $D = 0$; State vector, $X = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$; Input vector, $U = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$; Output vector,

$Y = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$. The time constants are calculated using Equation (7).

$$T_i = \frac{A_i}{a_i}\sqrt{\frac{2h_i^0}{g}}, \quad i = 1, \dots, 4 \tag{7}$$

The parameter values and steady state operating points of the process are assumed as per the system given in literature [4] and they are presented in Table 1 and Table 2 respectively.

Table 1. Process parameters

Area of Tank 1 and 3 (A_1, A_3)	*28* cm^2
Area of Tank 2 and 4 (A_2, A_4)	*32* cm^2
a_1, a_3	*0.071* cm^2
a_2, a_4	*0.057* cm^2
K_c	*0.5 V/cm*

Table 2. Steady state operating points

Steady state parameters	*Minimum Phase*	*Non minimum Phase*
h_1^0, h_2^0 $[cm]$	$(12.4, 12.7)$	$(12.6, 13)$
h_3^0, h_4^0 $[cm]$	$(1.8, 1.4)$	$(4.8, 4.9)$
v_1^0, v_1^0 $[V]$	$(3.00, 3.00)$	$(3.15, 3.15)$
k_1, k_2 $[cm^3/Vs]$	$(3.33, 3.35)$	$(3.14, 3.29)$
γ_1, γ_2	$(0.70, 0.60)$	$(0.43, 0.34)$

Substituting these values in the above equations, matrices A, B and C are computed. The transfer function matrices are obtained using MATLAB function and are given in Equations (8) and (9) for minimum phase and non-minimum phase operating points respectively.

$$G_-(s) = \begin{bmatrix} \frac{2.6}{1+62s} & \frac{1.5}{(1+23s)(1+62s)} \\ \frac{1.4}{(1+30s)(1+90s)} & \frac{2.5}{1+90s} \end{bmatrix} \tag{8}$$

$$G_+(s) = \begin{bmatrix} \frac{1.5}{1+63s} & \frac{2.5}{(1+39s)(1+63s)} \\ \frac{2.5}{(1+56s)(1+91s)} & \frac{1.6}{1+91s} \end{bmatrix} \tag{9}$$

The transfer matrix G has two zeros, one of them is always in the left half of s-plane, but the other can be located either in left half or right half of the s-plane based on the position of three way valves. So, the system is in minimum phase, if the values of γ_1 and γ_2 satisfy the condition $0 < \gamma_1 + \gamma_2 < 1$ and is in non-minimum phase, if the values of γ_1 and γ_2 satisfy the condition $1 < \gamma_1 + \gamma_2 < 2$.

3. **Design of Ideal Decoupler.** A popular approach to deal with control loop interactions is to design non-interacting or decoupling control schemes. The objective of this control is to eliminate the effects of loop interactions completely. This is achieved through the specification of compensation network known as "Decoupler". The role of decoupler is to decompose a multivariable process into several independent single-loop sub-systems. If such a controller is designed, complete or ideal decoupling occurs and the multivariable process can be controlled using independent loop controllers [5]. Figure 2 shows the general decoupling control structure.

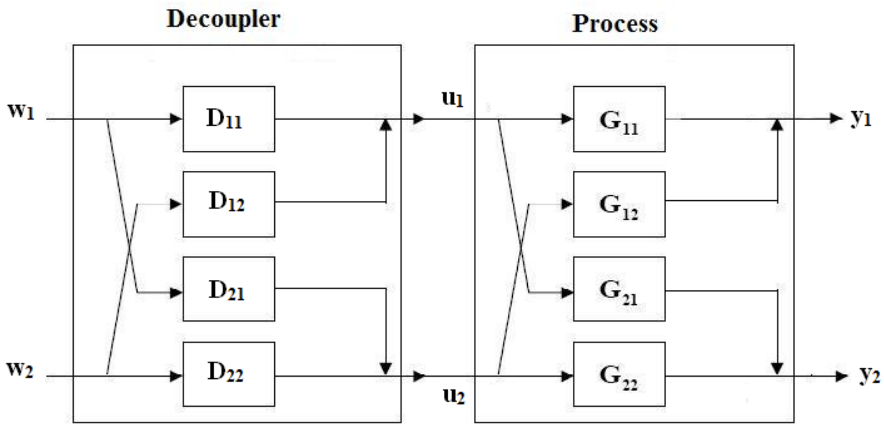


FIGURE 2. Architecture of system with decoupler

Ideal decoupler is selected because the decoupling elements are independent of the forward path controllers and therefore on line tuning of the controllers does not require redesign of the decoupler elements. Moreover, this technique can address both servo and regulator problem because decoupling occurs between the forward path control signals and the process levels and not between the set points and the outputs.

The ideal decoupler is designed by the method of Zalkind and Luyben in [6] as given in Equation (10).

$$D(s) = \begin{bmatrix} D_{11} & D_{12} \\ D_{21} & D_{22} \end{bmatrix} \tag{10}$$

where the diagonal elements, $D_{11} = D_{22} = 1$ (for ideal decoupler) and off diagonal elements, $D_{12} = -\frac{G_{12}D_{22}}{G_{11}}$ and $D_{21} = -\frac{G_{21}D_{11}}{G_{22}}$.

The decoupler matrices designed for minimum phase and non minimum phase systems are given in Equations (11) and (12) respectively.

$$D_s = \begin{bmatrix} 1 & \frac{-0.577}{(1+23s)} \\ \frac{-0.5}{(1+30s)} & 1 \end{bmatrix} \tag{11}$$

$$D_+(s) = \begin{bmatrix} 1 & \frac{-1.667}{(1+39s)} \\ \frac{-1.5625}{(1+56s)} & 1 \end{bmatrix} \tag{12}$$

4. **Relative Gain Array.** For designing control system for MIMO systems with interactions, it is required to select proper input-output pairing. To determine proper pairs it is essential to evaluate the degree of interaction between variables. The Relative Gain Array (RGA) concept is employed to determine the input-output pairing for both minimum phase and non minimum phase conditions [7].

According to the proposal given by Bristol [8], RGA is given by Equation (13)

$$\wedge = \begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \end{bmatrix} \tag{13}$$

For minimum phase system λ_{11} is obtained as 0.63 which falls in the range $0.5 < \lambda_{11} < 1$, so the pairing is determined as $y_1 - u_1$ and $y_2 - u_2$. However, for the non minimum phase system λ_{11} is obtained as 0.375 which falls in the range $0 < \lambda_{11} < 0.5$, so the suitable pairing is found as $y_1 - u_2$ and $y_2 - u_1$.

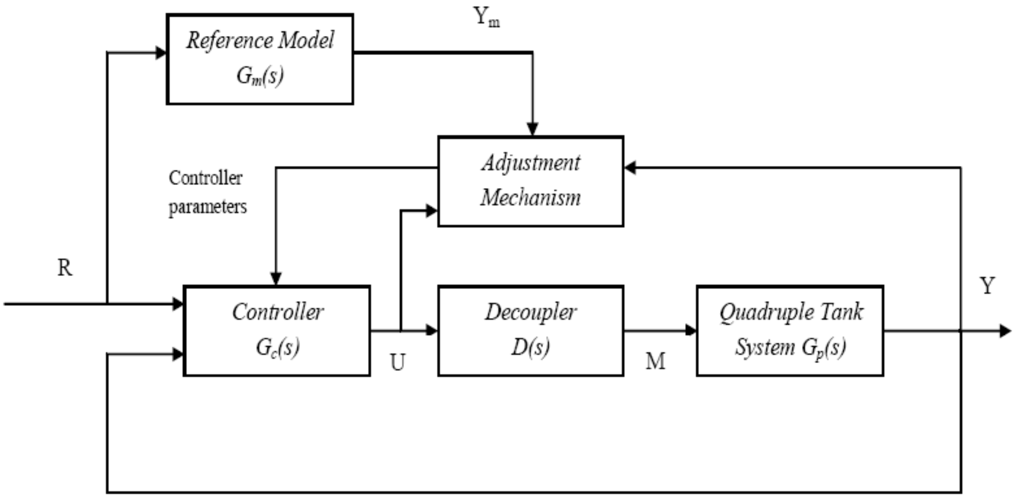


FIGURE 3. Structure of MRAC based control system for QTS

5. **Model Reference Adaptive Control.** This is an adaptive control technique where the performance specifications are given in terms of a reference model. The model is selected in such a way that it gives the ideal response of the process which is desired. The controller parameters are automatically adjusted by the adaptation mechanism in such a way that the performance of the process output matches with that of the model as referred in [9,10]. The block diagram of the proposed control structure using adaptive control technique is given in Figure 3.

The architecture of adaptive controller has two loops:

(1) The inner loop is the simple feedback loop consisting of the process, decoupler and the controller.

(2) The outer loop is employed to adjust the controller parameters in such a way that the deviation between actual process output and that of the reference model is small.

For the first order process the adaptation laws are framed based on the MIT rule as follows:

For Process

$$\frac{dy}{dt} = -ay + b \tag{14}$$

For the Model

$$\frac{dy_m}{dt} = -a_m y_m + b_m \tag{15}$$

For the Controller

$$u = \theta_1 u_c - \theta_2 y \tag{16}$$

The cost function for adaptation is given by

$$J(\theta) = \frac{1}{2}e^2(\theta) \tag{17}$$

where $e = y - y_m$.

MIT rule with negative gradient approach is given by the following expression

$$\frac{d\theta}{dt} = -\gamma\frac{\delta J}{\delta\theta} = -\gamma e\frac{\delta e}{\delta\theta} \tag{18}$$

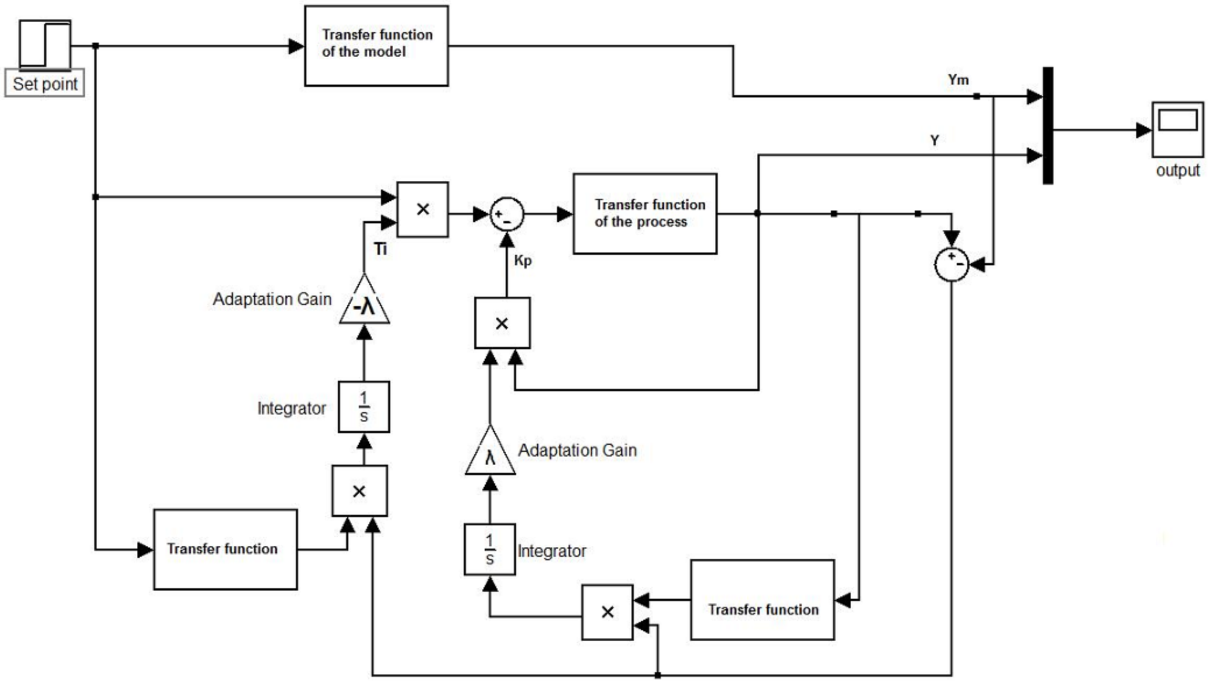


FIGURE 4. Adaptation mechanism for a single control loop using MRAC

From the MIT rule and Equation (17) the adaptation laws can be found in terms of the original controller parameters as follows:

$$\frac{d\theta_1}{dt} = -\gamma e u_c \tag{19}$$

$$\frac{d\theta_2}{dt} = -\gamma e y \tag{20}$$

where θ_1 and θ_2 are K_p and T_i in this case because the PI algorithm is used as the controller here.

The block diagram of adaptation control mechanism using MRAC is shown in Figure 4.

The following expressions (21) and (22) are obtained as decoupled transfer function matrix for minimum phase and non minimum phase operating points respectively.

$$GD_-(s) = \begin{bmatrix} \frac{2}{1+62s} & 0 \\ 0 & \frac{1.85}{1+42s} \end{bmatrix} \tag{21}$$

$$GD_+(s) = \begin{bmatrix} \frac{5.4}{1+146s} & 0 \\ 0 & \frac{2.4}{1+64s} \end{bmatrix} \tag{22}$$

It has been noted that the two input two output quadruple tank system is now considered as two SISO systems acting without interactions. To control these processes two PI controllers are employed. The controller parameters K_p and T_i are automatically adjusted to force the process outputs (levels) as specified by the reference model.

The reference model is selected in such a way to get the closed loop response with overshoot 10% and settling time 10 sec. The adaptation gains (λ) are selected as given in Table 3.

Table 3. Adaptation gain values for both the operating points

	λ Values	
	For adapting K_p	*For adapting T_i*
PI Controller for Level 1	*5000*	*1000*
PI Controller for Level 2	*3000*	*1000*

6. **Particle Swarm Optimization.** PSO is a biologically-inspired algorithm motivated by a social analogy to approach a convenient solution (or set of solutions) for a problem. The particle swarm concept originated as a simulation of simplified social system. The original intent was to graphically simulate the choreography of bird of a bird block or fish school. However, it was found that particle swarm model can be used as an optimizer [11].

PSO is used as a combinatorial metaheuristic technique to solve the optimization problems. In PSO, each single solution is a "bird" in the search space which is called as "particle". All the particles have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles.

This algorithm is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. This fitness value is stored in the workspace and it is called as 'local best position'. Another "best" value that is tracked by the particle swarm optimizer is the best value obtained so far by any particles in the population. This best value is called as 'global best position'. After finding these two best values, the particle updates its velocity and positions with the following Equations (23) and (24).

$$v_{i,m}^{t+1} = wv_{i,m}^{t} + C_1 * rand() * (pbest_{i,m} - x_{i,m}^{t}) + C_2 * rand() * (gbest_m - x_{i,m}^{t}) \tag{23}$$

$$x_{i,m}^{t+1} = x_{i,m}^{t} + v_{i,m}^{t+1} \tag{24}$$

$i = 1, 2, \ldots, n$
$m = 1, 2, \ldots, d$
where
n: Number of particles in the group
d: Dimension
t: Pointer of iteration
$v_{i,m}^{t+1}$: Velocity of particle I at iteration t
w: Inertia weight factor
c_1, c_2: Acceleration Constants
$rand()$: Random number between 0 and 1
$x_{i,d}^{t}$: Current position of particle i at iterations
$pbest_i$: Best previous position of the ith particle
$gbest$: Best particle among all the particles in the population

The flow chart for the algorithm is given in Figure 5.

To design PI controller for the QTS, Integral of squared error (ISE) is used as the cost function, which has to be minimized by the optimal selection of the controller parameters. In the proposed PSO method each particle contains two members K_p and K_i. It means that the search space has two dimensions and particles must 'fly' in a two dimensional space [12,13]. For this study, the following values are used for optimization the controller parameters using PSO.

Population size = 10
W = 0.7
C1 = 1.5
C2 = 1.5
Iterations = 10

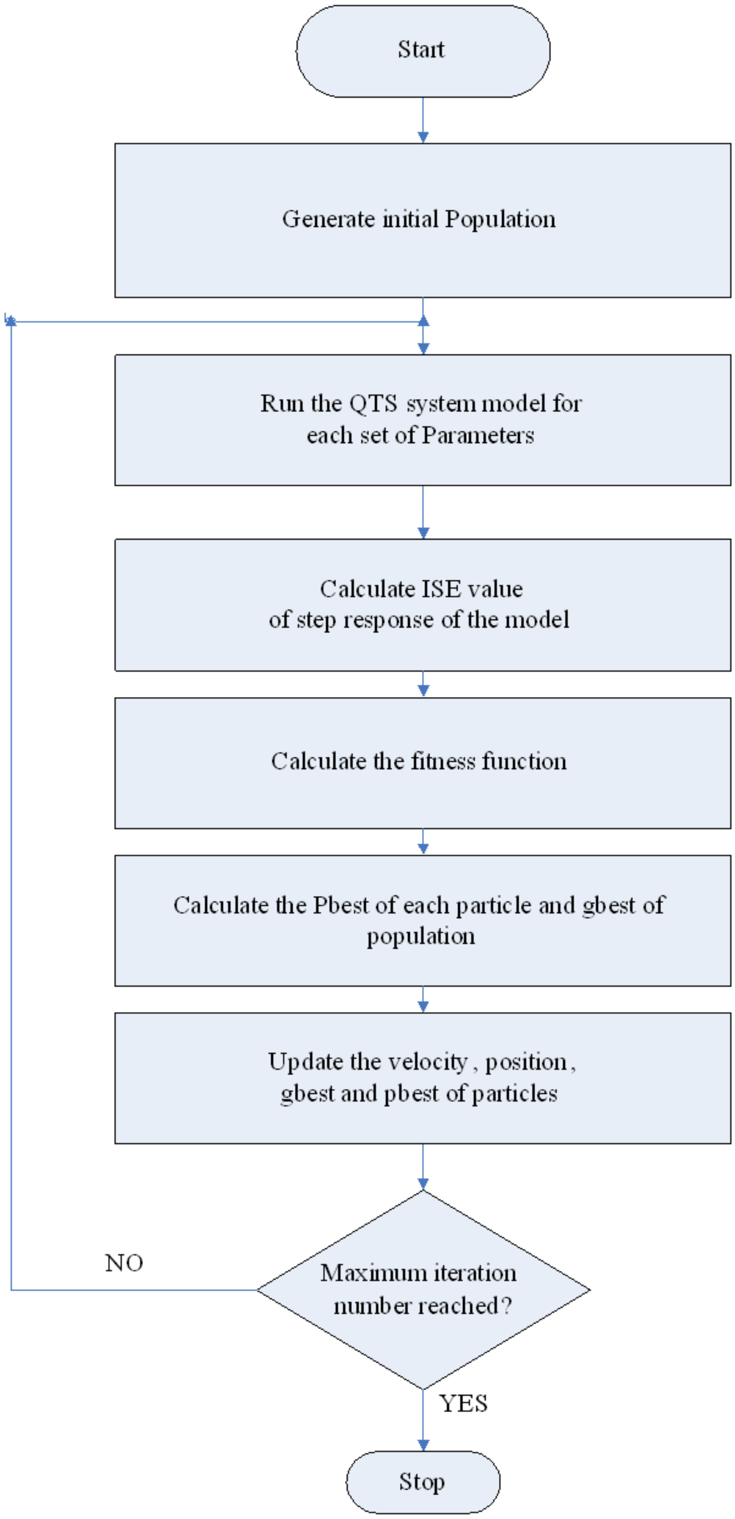


FIGURE 5. Flow chart for PSO algorithm

7. **Results and Discussions.** The designed controller for the multivariable process is implemented using MATLAB/SIMULINK toolbox presented in [15] and the following results are obtained. The responses of the quadruple tank process for both minimum phase and non minimum phase operating points are obtained using ZN tuned simple PI controller, ZN tuned decoupled PI controller, auto tuned decoupled PI controller using MRAC and optimized decoupled PI controller using PSO. The minimum phase responses are shown in Figures 6-9 while the non minimum phase responses are shown in Figures 10-13. In all the graphs X axis denotes Time in seconds and Y axis denotes Level in centimeters.

Comparing the responses for minimum phase condition, simple PI controller with conventional tuning is not immune to the interactions caused by the other input variable. Using decoupler, the immunity and hence the performance gets improved because the system is entirely decoupled and the variables are independent of each other. Thus, the system is resilient so that any changes occurred in one input will not affect the output of the other one.

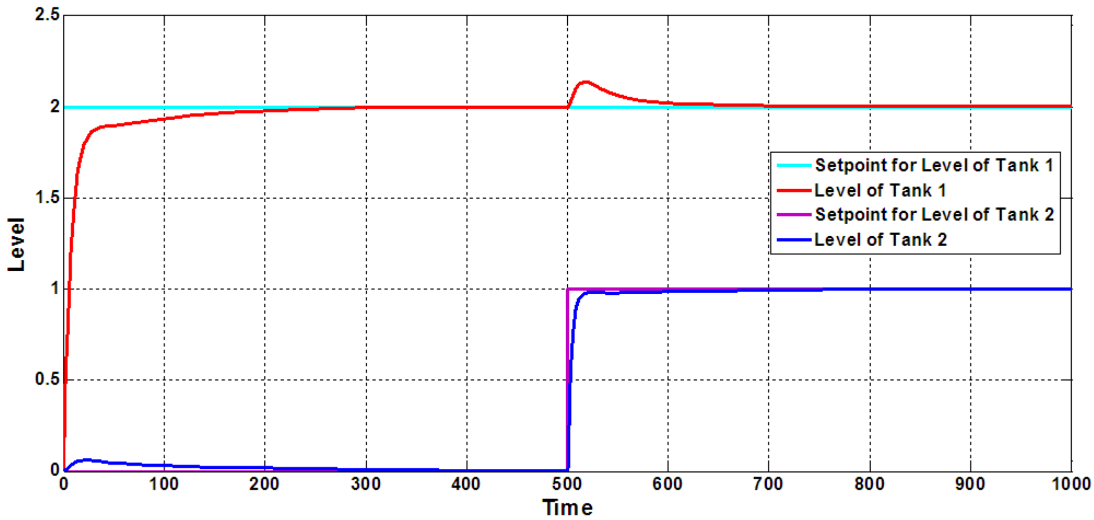


FIGURE 6. Response of PI controller in minimum phase

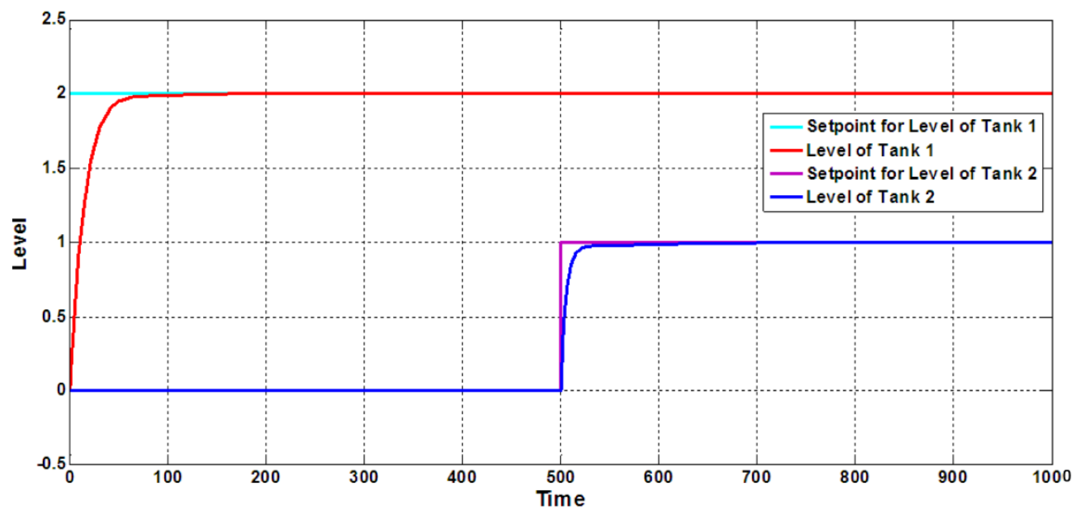


FIGURE 7. Response of PI controller with decoupler in minimum phase

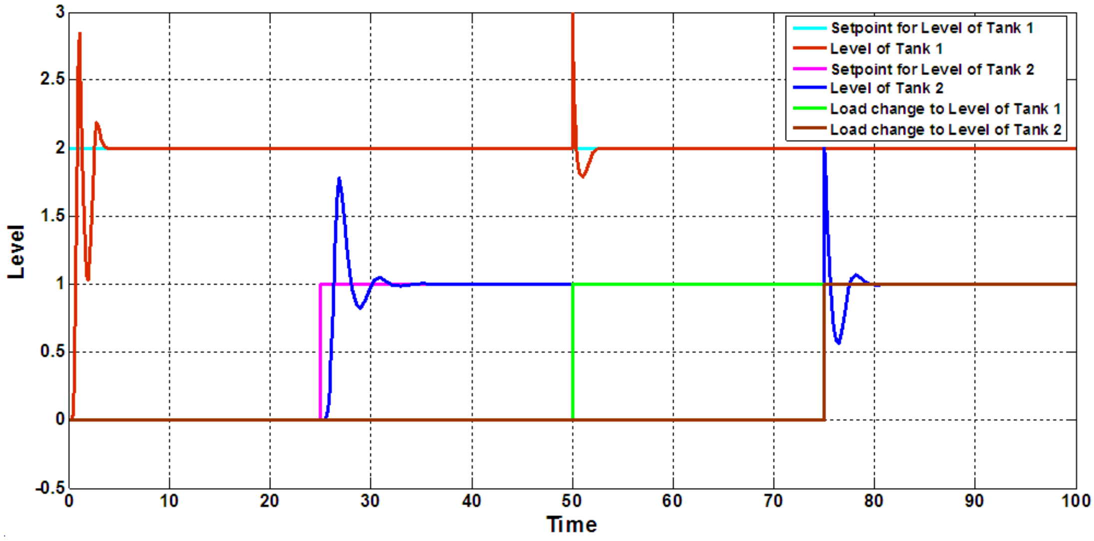
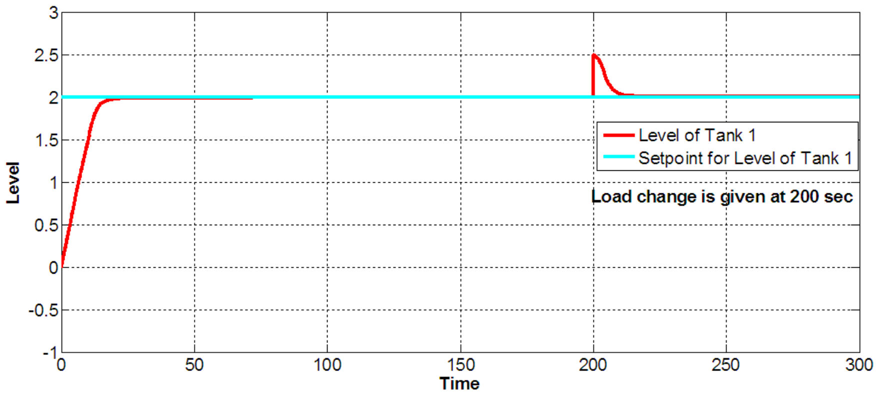
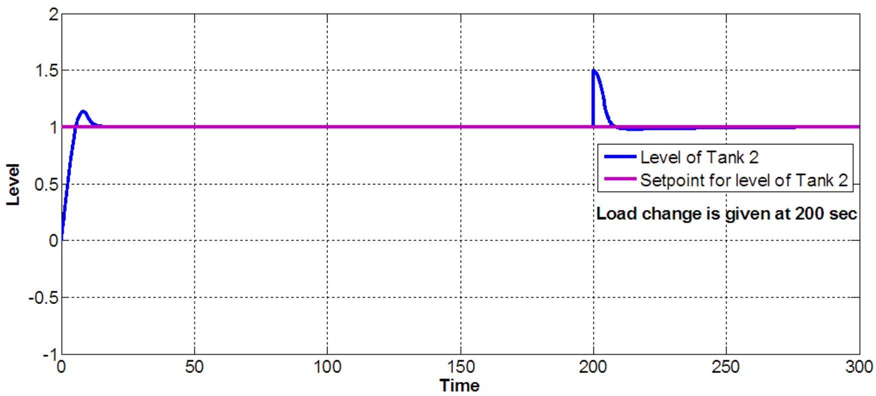


FIGURE 8. Response of PI controller with MRAC in minimum phase



(a)



(b)

FIGURE 9. (a) Response of the PSO tuned PI controller for Tank level '1' in minimum phase. (b) Response of the PSO tuned PI controller for Tank level '2' in minimum phase.

It is observed from Figure 10 that the process exhibits inverse response when it is operated in non minimum phase condition and hence it is not possible to provide a better control to the process with simple PI controller in this operating condition.

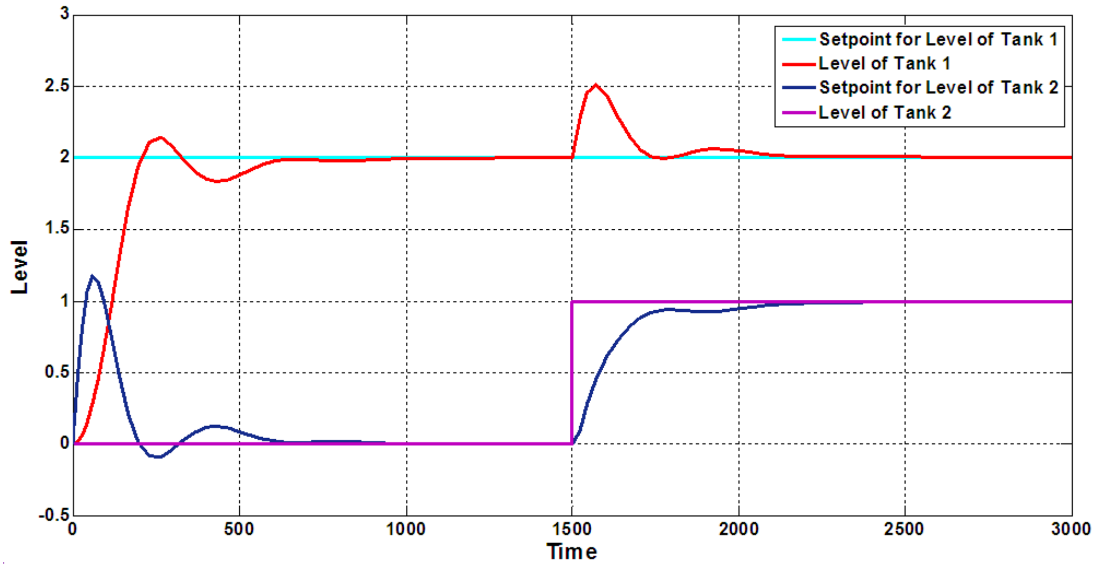


FIGURE 10. Response of PI controller in non minimum phase

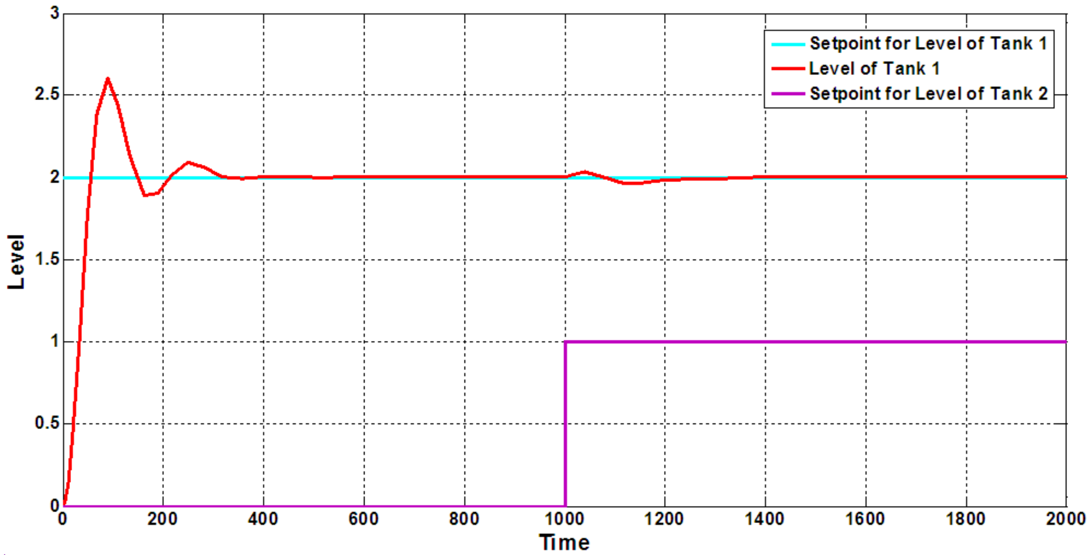


FIGURE 11. Response of PI controller with decoupler in non minimum phase

From the graphs of Figures 8 and 12, it has been observed that the adaptive decoupled controller using MRAC, strongly suppresses the interactions in both the operating conditions and guarantees robust performance, but the overshoots are there in the response. Proper selection of the adaptation gain may lead to the reduction in overshoot.

The responses for optimized PI controller with decoupler are given in Figures 9 and 13. It is also observed that the PSO tuned PI controller gives optimal response and hence guarantees the robustness and resilience which has been proved in the quantitative comparison of parameters for these controllers. Moreover, the response time is faster and settling time is shorter without penalizing the overshoot in this case.

Table 4 presents the quantitative comparison of the performances of conventional PI controller, decoupled PI controller, adaptive decoupled PI controller and optimized decoupled PI controller.

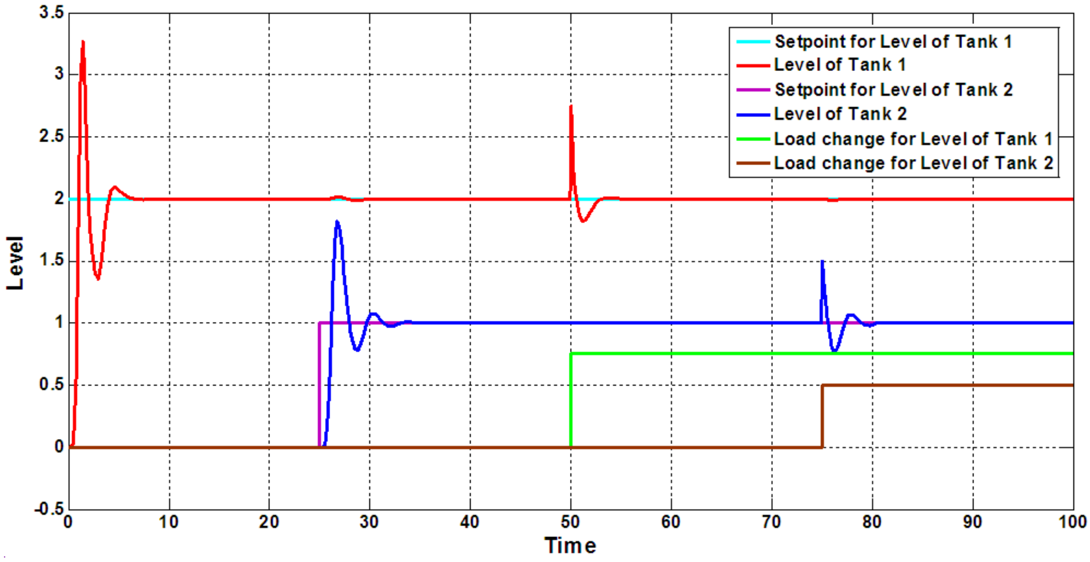
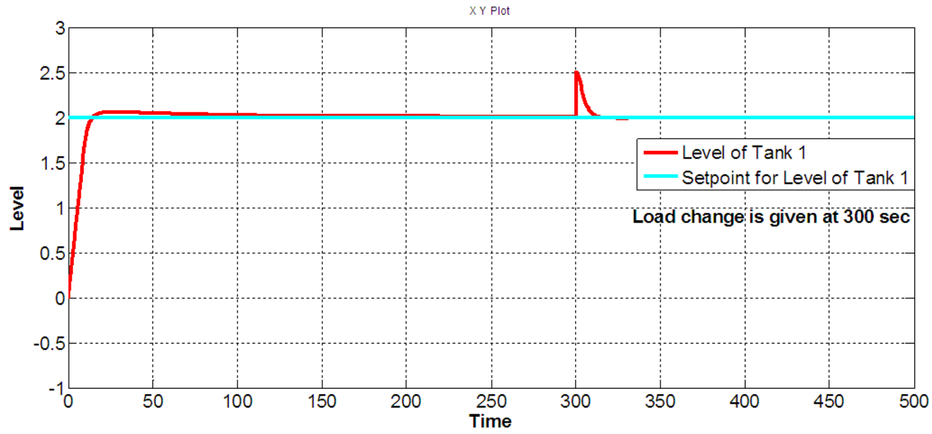


FIGURE 12. Response of the PI controller with MRAC in non minimum phase

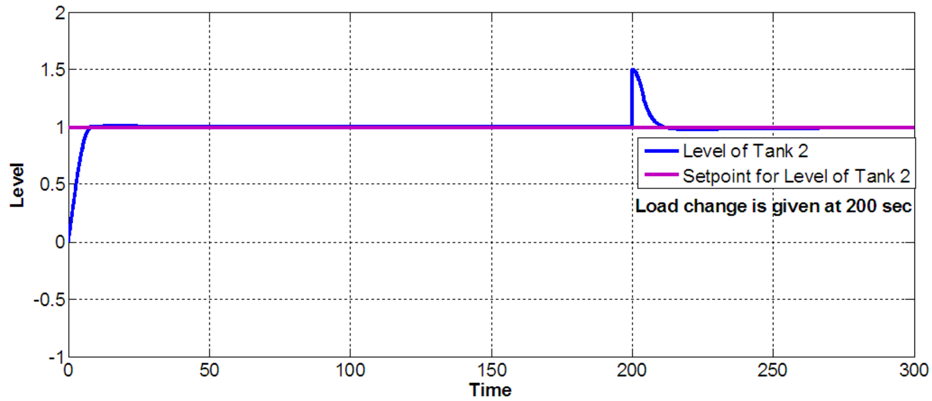
TABLE 4. Quantitative comparison of controller performance

Operating Points		Parameters	Controller			
			PI Controller	Decoupled PI Controller with ZN tuning	Adaptive PI Controller using MRAC	Decoupled PI Controller with PSO
Minimum Phase	Level 1	Settling Time (sec)	250	90	6	22
		Peak Overshoot	1%	1%	30%	0%
		Rise Time (sec)	15	12	2	10
		ISE	14.2678	12.2314	3.2360	5.4055
	Level 2	Settling Time (sec)	150	50	8	12
		Peak Overshoot	2%	2%	70%	15%
		Rise Time (sec)	10	10	1	4
		ISE	1.8310	3.8706	1.7499	1.7817
Non minimum Phase	Level 1	Settling Time (sec)	1380	600	7	147
		Peak Overshoot	10%	30%	30%	5%
		Rise Time (sec)	240	80	3	10
		ISE	35.8263	9.1461	1.5426	15.0047
	Level 2	Settling Time (sec)	1380	800	10	8
		Peak Overshoot	25%	20%	40%	0%
		Rise Time (sec)	210	65	2	6
		ISE	211.8629	170.5489	4.2465	1.8645

8. **Conclusion.** In this paper, the design of optimized PI controller using PSO algorithm and its performance in comparison with conventional adaptive technique for quadruple tank process has been described. The linearized model of QTS has a multivariable transmission zero and it is much more difficult to control the system in non minimum phase



(a)



(b)

FIGURE 13. (a) Response of the PSO tuned PI controller for Tank level '1' in non minimum phase. (b) Response of PSO tuned PI controller for Tank level '2' in non minimum phase.

condition than in minimum phase condition. Similar multivariable processes are very common in industrial processes such as Boiler turbine system, Distillation process in Petrochemical industries, CSTR in chemical process industries.

In multivariable controller design, a choice must be made between performance and robustness. Both performance and robustness are functions of the process being controlled, the selection of the controller and the tuning of the controller parameters. The proposed control system can directly address this problem by optimizing the controller parameters and it has been proved through simulation via the bench mark QTS. However, proper design of the final control elements and actuators are essential to support this concept without saturation problem.

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