Comparison of PI controller tuning using GA and PSO for a Multivariable Experimental Four Tank System

Deepa Thangavelusamy [#1], Lakshmi Ponnusamy [*2]

[#] Department of Electrical and Electronics Engineering
Anna University, Chennai, India.
[1] deepabalaji30@gmail.com
[*] Department of Electrical and Electronics Engineering
Anna University, Chennai, India
[2] lakshmi_p_2000@yahoo.com

***Abstract*— This paper presents a design procedure for a Particle Swam Optimization (PSO) based PI and investigates the robustness of the PSO technique in the Quadruple Tank Process (QTP). From the open loop response, the transfer function is derived. Design of a Decentralized PI Control and tuning the PI parameters using Genetic Algorithm (GA) and PSO techniques are discussed. Performance index ISE is used for designing the controllers. The results show that PSO controller is robust for both servo and regulatory responses.**

Keyword-Four tank System, Decentralized PI, GA and PSO

I. Introduction

The multivariable zero dynamics of the system can be made both minimum phase and non-minimum phase by simply changing a valve. This makes the four tank system suitable for illustrating many concepts in linear and nonlinear multivariable control [1]. Designing multivariable decoupling and multiloop Proportional Integral (PI) / Proportional Integral Derivative (PID) controllers in a sequential manner were developed [2]. The method is based on a single-loop tuning technique developed for multivariable systems with unknown dynamics.

Tan et al [3] proposed PID tuning is based on loop shaping H_∞ control. A method for auto-tuning fully cross-coupled multivariable PID controllers from decentralized relay feedback is proposed [4]. It should be noted that modern control techniques might achieve better performance than the conventional PID controller. Zhuang and Atherton [5] designed a diagonal PID controller tuning using an integral performance optimization procedure for a Two Input Two Output (TITO) system.

Genetic Algorithm (GA) has been demonstrated to be an appropriate tool for parameters optimization tasks and they have been used with good results. GA is a search technique used to find good solutions to optimization and search problems. They belong to a particular class of evolutionary algorithms that use techniques inspired by evolutionary biology such as inheritance, mutation, selection and crossover. A good solution is found by the GA providing a parametric fitness function to minimize [6].

Dimeo, and Lee [7] discussed the application of a genetic algorithm to control system design for a boiler-turbine plant. The improved genetic algorithm for identifying multi-variables nonlinear boiler model of 300MW power unit is introduced [8]. In this algorithm, floating-point coding, rank - based selection, elitist reservation and grouping method are used, and the premature convergence is restrained, and the searching ability is improved.

GAs and Neural Networks are adaptive optimization method based on biological principles [9]. These problems include optimizing the weighted connections in feed-forward neural networks using both binary and real-valued representations, and using a genetic algorithm to discover novel architectures in the form of connectivity patterns for neural networks that learn using error propagation.

Application of the GA to an optimal control problem entails minimizing the Integral Squared Error (ISE) of the input and states [10]. Yuen [11] proposed by interacting with a dynamically constructed Binary Space Partitioning archive (BSP). The concept of BSP originates from the fields of computer graphics and computational geometry. The BSP archive is built up as a random tree for which its growth process reflects the evolution history of the GA, and is a quick method to query whether there is a revisit.

Dongmei Zhang et al [12] proposed an improved genetic algorithm based on simplex crossover operator is used for the parameter optimization for support vector regression to make the crossover operation obtain the gradient, to make an adjustment through linear computing in the parameters, which are beyond the constraint scope after the reflection, expansion, and compression operation on the simplex operator, and to introduce the crossover validation strategy into the design of fitness function of genetic algorithm to improve the algorithm's generalization performance.

Design of frequency selective surface using Particle Swarm Optimization (PSO) technique is discussed [13] and [14]. The PSO algorithm is the population based optimization algorithm which can be used to solve the minimization problem [15]. Sadeghierad et al [16] presented the optimal design of high speed axial flux generator. The GA and PSO are used for optimizing the efficiency of machine.

Bouzid Mhamdi et al [17] proposed the algorithm that integrates the main features of GA and PSO into the optimization process to solve the complicated scattering inverse problem. Particle swarm optimization technique has been used for tuning of neural networks utilized for carrying out both forward and reverse mappings of metal inert gas (MIG) welding process [18].

A.M. El-Zonkoly [19] proposed a multi-objective index-based approach for optimally determining the size and location of multi-Distributed Generation (multi-DG) units in distribution systems with different load models. It is shown that the load models can significantly affect the optimal location and sizing of DG resources in distribution systems. The proposed function also considers a wide range of technical issues such as active and reactive power losses of the system, the voltage profile, the line loading, and the Mega Volt Ampere (MVA) intake by the grid. An optimization technique based on particle swarm optimization (PSO) is introduced.

The outline of the paper is as follows. A nonlinear model for the four tank system based on physical data is derived in section 2. Simple multi-loop PI control of the system using GA and PSO are discussed in section 3. The results and conclusions are presented in sections 4 and 5 respectively.

II. PHYSICAL MODEL

A schematic diagram of the process is shown in Figure. 1. The target is to control the level in the lower two tanks with two pumps. The process inputs are input voltages to the two pumps and the outputs are the level measurements.

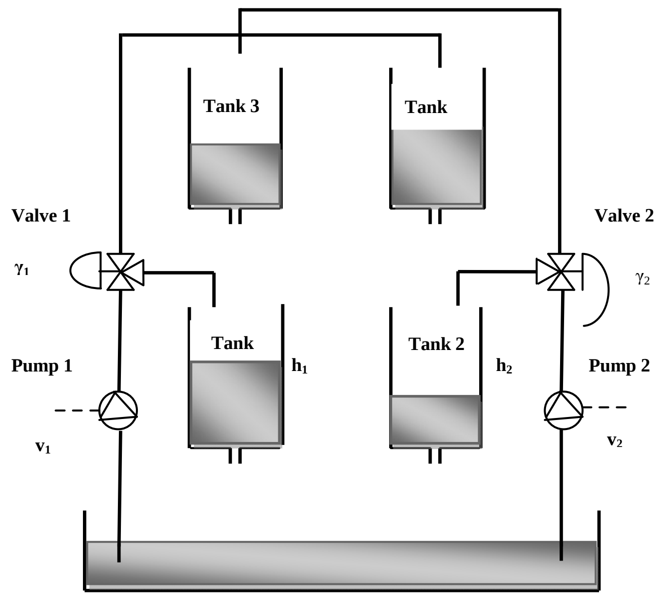

Figure. 1. Schematic diagram of the four tank system

The voltage applied to pump i is v_i and the corresponding flow is $k_i v_i$. The parameters γ_1, γ_2 ε (0,1) are determined from the position of the valves set prior to an experiment. The flow to Tank 1 is $\gamma_1 k_1 v_1$ and the flow to Tank 4 is $(1-\gamma_1)k_1 v_1$ and the same applies to Tank 2 and Tank 3. The acceleration of gravity is denoted as g. The measured level signals are $k_c h_1$ and $k_c h_2$.

Mass balances and Bernoulli's law yield the following simple nonlinear equations [1]

$$\frac{dh_1}{dt} = -\frac{a_1}{A_1}\sqrt{2gh_1} + \frac{a_3}{A_1}\sqrt{2gh_3} + \frac{\gamma_1 k_1}{A_1}v_1$$

$$\frac{dh_2}{dt} = -\frac{a_2}{A_2}\sqrt{2gh_2} + \frac{a_4}{A_2}\sqrt{2gh_4} + \frac{\gamma_2 k_2}{A_2}v_2$$

$$\frac{dh_3}{dt} = -\frac{a_3}{A_3}\sqrt{2gh_3} + \frac{(1-\gamma_2)k_2}{A_3}v_2 \qquad (1)$$

$$\frac{dh_4}{dt} = -\frac{a_4}{A_4}\sqrt{2gh_4} + \frac{(1-\gamma_1)k_1}{A_4}v_1$$

where

A_i	:	Cross-section of Tank i
a_i	:	Cross-section of the outlet hole i
h_i	:	Water level i

The linearized state-space equation is given by

$$\frac{dx}{dt} = \begin{bmatrix} -\frac{1}{T_1} & 0 & \frac{A_3}{A_1T_3} & 0 \\ 0 & -\frac{1}{T_2} & 0 & \frac{A_4}{A_2T_4} \\ 0 & 0 & -\frac{1}{T_3} & 0 \\ 0 & 0 & 0 & -\frac{1}{T_4} \end{bmatrix} x + \begin{bmatrix} \frac{\gamma_1 k_1}{A_1} & 0 \\ 0 & \frac{\gamma_2 k_2}{A_2} \\ 0 & \frac{(1-\gamma_2)k_2}{A_2} \\ \frac{(1-\gamma_1)k_1}{A_4} & 0 \end{bmatrix} u$$

$$y = \begin{bmatrix} k_c & 0 & 0 & 0 \\ 0 & k_c & 0 & 0 \end{bmatrix} x \qquad (2)$$

where the time constants are

$$T_i = \frac{A_i}{a_i}\sqrt{\frac{2h_i^0}{g}}, i = 1,\ldots 4 \qquad (3)$$

The corresponding transfer function matrix is

$$G(s) = \begin{bmatrix} \frac{\gamma_1 c_1}{1+sT_1} & \frac{(1-\gamma_2)c_1}{(1+sT_3)(1+sT_1)} \\ \frac{(1-\gamma_1)c_2}{(1+sT_4)(1+sT_2)} & \frac{\gamma_2 c_2}{1+sT_2} \end{bmatrix} \qquad (4)$$

where $c_1=T_1k_1k_c/A_1$ and $c_2=T_2k_2k_c/A_2$.

Figure.2 shows the experimental setup of the Quadruple Tank Process (QTP) consisting of four interconnected tanks with common water source. This setup is interfaced with a window - based PC via interfacing modules and USB ports. This setup consists of a water supply tank with two positive displacement pumps for water circulation, two pneumatic control valves, four transparent process tanks fitted with level transmitters and rotameters (0-440 lph). Process signals from the level transmitters are interfaced with the PC and it sends outputs to the individual control valves through interfacing units using LabVIEW software. Tanks 1 and 2 are mounted below the other two tanks 3 and 4 for receiving water flow by gravity. Each tank outlet opening is fitted with a valve. Both pumps 1 and 2 takes water by suction from the reservoir. Flow from the pumps is split to top and bottom tanks by manually adjusting the valves. Ratio of flow split between the top and bottom tanks, substantially alters the dynamics of the system. Pump 1 discharges water to tank 1 and tank 4 simultaneously and the flows are indicated by rotameters 1 and 4. Similarly, pump 2 discharges water to tank 2 and tank 3 and the flows are indicated by rotameters 2 and 3. Tanks 1 and 2 also receive water by gravity flow from tank 4 and tank 3, respectively.

Figure. 2. Experimental setup of the four tank system

The parameters of QTP are given in Table 1.

TABLE 1
PROCESS PARAMETER VALUES OF Fig.1

i	$A_i(cm^2)$	$a_i(cm^2)$	h_i^0 (cm)
1	176.71	2.01	6.34
2	176.71	2.01	8.31
3	176.71	2.01	3.06
4	176.71	2.01	4.16

The time constants are T_1=42.48 sec, T_2=55.64 sec, T_3=39.86 sec and T_4=55.68 sec.
The transfer function matrix is given in (5)

$$G(s)=\begin{bmatrix} \dfrac{0.3811}{42.48S+1} & \dfrac{0.2334}{(42.48S+1)(39.86S+1)} \\ \dfrac{0.1998}{(55.68S+1)(55.64S+1)} & \dfrac{0.3934}{55.68S+1} \end{bmatrix} \tag{5}$$

Relative Gain Array (RGA)

The RGA was introduced by Ed Bristol as a measure of interaction in multivariable control systems [16]. The RGA Λ is defined as

$$\Lambda = G(0)\times G^{-T}(0) \tag{6}$$

where $\times$ denotes the element by element matrix multiplication and $^{-T}$ inverse transpose.
Properties of RGA:

1. Sum of rows and columns property of the RGA
   Each row of the RGA sums to 1.0 and each column of the RGA sums to 1.0.

   (ie) $\lambda_{11}+\lambda_{12}=1$ $\quad$ $\lambda_{11}+\lambda_{21}=1$
   $\lambda_{12}+\lambda_{22}=1$ $\quad$ $\lambda_{21}+\lambda_{22}=1$

2. Use of RGA to determine variable pairing.
   It is desirable to pair output i and input j such that λ_{ij} is as close to 1 as possible.

The RGA depends only on the valve settings and not on other physical parameters.

$$\text{RGA } \Lambda=\begin{bmatrix} 1.4515 & -0.4515 \\ -0.4515 & 1.4515 \end{bmatrix}$$

From RGA h_1 is paired with u_1 and h_2 is paired with u_2

III. DECENTRALIZED PI CONTROL

The decentralized controller structure is shown in Figure.3 and the decentralized control law [4] u=diag{C_1,C_2}(r-y) .

The QTP is considered as minimum phase process (the process does not have RHP zeros or time delays).
PI controllers have the form [20]

$$C_l(s) = K_l\left(1+\frac{1}{T_{il}s}\right), \quad l = 1,2 \tag{7}$$

So the direct synthesis controller for a first order process gives

$$K_l = \frac{T_{il}}{K_P T_c}$$
$$T_c = 0.5T_{il} \tag{8}$$

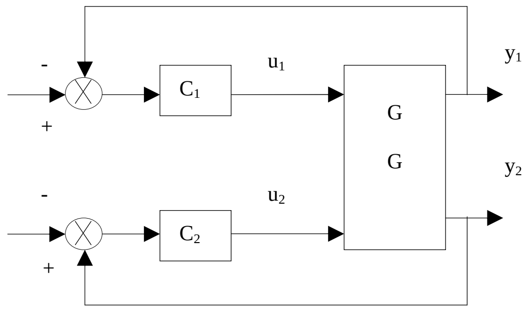

Figure.3 Decentralized control structure with two PI controllers

3.1 Genetic Algorithm

The most popular technique in evolutionary computation research has been the genetic algorithm [7]. An initial population of step response data is created. The fitness is evaluated through some appropriate measure. The algorithm is driven towards maximizing this fitness measure. For example, in a function maximization problem the fitness measure might be the function evaluation itself. Application of the GA to an optimal control problem entails minimizing the ISE of the input and states. After the fitness of the entire population has been determined, it must be determined whether or not the termination criterion has been satisfied. This criterion can be any number of things. One possibility is to stop the algorithm at some finite number of generations and designate the result as the best fit from the population. Another possibility is to test if the average fitness of the population exceeds some fraction of the best fit in the population. If the criterion is not satisfied then continue with the three genetic operators. Next, the three genetic operations of reproduction, crossover, and mutation are invoked. Fitness-proportionate reproduction is effected thought the simulated spin of a weighted roulette wheel.

The roulette wheel is biased with the fitness of each of the solution candidates. The wheel is spinned N times where N is the number of strings in the population. This operation yields a new population of strings that reflect the fitness of the previous generation's fit candidates. The next operation, crossover, is performed on two strings at a time that are selected from the population at random. Crossover involves choosing a random position in the two strings and swapping the bits that occur after this position. In one generation the crossover operation is performed on a specified percentage of the population. This proportion of the population is specified at the initialization stage of the algorithm. The final genetic operator in the algorithm is mutation. Mutation is performed sparingly, typically every 100- 1000 bit transfers from crossover, and it involves selecting a string at random as well as a bit position at random and changing it from a 1 to a 0 or vice-versa. After mutation, the new generation is complete and the procedure begins again with fitness evaluation of the population.

In a control system design using the GA the parameters that are represented as binary strings are the relevant control parameters. In the design of the PI control system, the parameters are the two proportional, integral controller illustrated in Figure 3.

The GA based PI parameters are tuned using MATLAB software and these values are applied to experimental set up of four tank process. The objective function (F) considered is based on the error criterion (9). The controller performance is evaluated in terms of ISE given by,

$$ISE = \int_0^t (h_{1ref} - h_1)^2 dt + (h_{2ref} - h_2)^2 dt \qquad (9)$$

The following GA parameters are selected for the training cycle

Population Size	:	10
Selection	:	Roulette Wheel
Cross Over Rate	:	0.8
Mutation Rate	:	0.01
Generations	:	100
Population Type	:	Double

3.2 Particle Swarm Optimization

PSO is a robust stochastic optimization technique based on the movement and intelligence of swarms. PSO applies the concept of social interaction to problem solving. It was developed in 1995 by James Kennedy and Russell Eberhart. It uses a number of agents that constitute a swarm, moving around in the search space, looking for the best solution. Each particle is treated as a point in an N-dimensional space which adjusts its "flying" according to its own flying experience as well as the flying experience of other particles. Each particle keeps track of its coordinates, in the solution space, which are associated with the best solution that has achieved so far by that particle. This value is called personal best, pbest. Another best value that is tracked by the PSO is the best value obtained so far by any particle in the neighbourhood of that particle. This value is called gbest. The basic concept of PSO lies in accelerating each particle toward its pbest and the gbest locations, with a random weighted acceleration at each time step as shown in Figure 4.

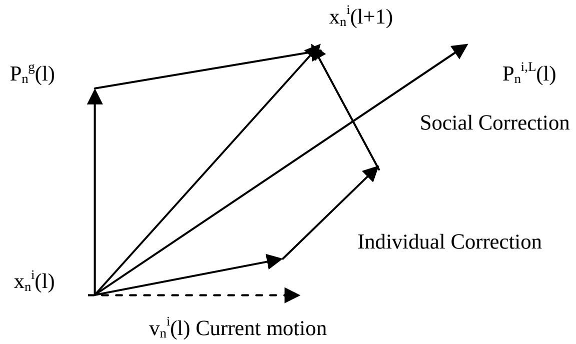

Figure. 4. Graphical representation of the mechanism of velocity update.

where

S^k	: current searching point.
S^{k+1}	: modified searching point.
V^k	: current velocity.
V^{k+1}	: modified velocity.
V_{pbest}	: velocity based on pbest.
V_{gbest}	: velocity based on gbest.

Each particle tries to modify its position using various informations, such as current positions, current velocities, the distance between the current position and pbest, and the distance between the current position and the gbest.

The modification of the particle's position can be mathematically modeled according to the following equation: $V_{ik} + 1 = wV_{ik} + c_1 rand1(\ldots) \times (pbest_i - s_{ik}) + c_2 rand2(\ldots) \times (gbest - s_{ik})$ (10)

where,

V_{ik}	: velocity of agent i at iteration k,
w	:weighting function,
c_j	: weighting factor,
rand	: uniformly distributed random number between 0 and 1,
s_{ik}	: current position of agent i at iteration k,
$pbest_i$	: pbest of agent i,
gbest	: gbest of the group.

The following weighting function is usually utilized in the equation (10)

$$w = w_{Max} - \left[\left(w_{Max} - w_{Min} \right) \times iter \right] / N \qquad (11)$$

where w_{Max} :initial weight,
w_{Min} :final weight,
N :maximum iteration number,
iter :current iteration number.

The new position is then determined by the sum of the previous position and the velocity

$$s_{ik+1} = s_{ik} + V_{ik+1} \qquad (12)$$

The flow chart of a general PSO algorithm [21] is developed. The optimal values of the conventional PI controller parameters K_p and K_i are found using PSO. Certain parameters of PSO need to be defined. The objective function (F) considered, is based on the error criterion (12). The controller performance is evaluated in terms of Integral Square Error (ISE) given in equation (9).

The PSO algorithm will compare the objective function evaluated at the new positions with the error criterion set by the user as illustrated in Figure.5. If the criterion is not satisfied, the random number generations will insure that different numerical values will be tried in the next update and the process can go on until the termination of the evaluation of the algorithm.

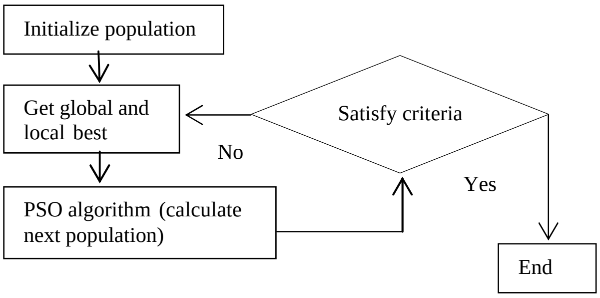

Figure. 5. Flow chart for the PSO algorithm

The following PSO parameters are selected for the training cycle for the QTP

Size of the swarm "no of birds"	n = 50;
Maximum number of "birds steps"	= 100;
PSO parameter C_1	c_1 = 0.4;
PSO parameter C_2	c_2 = 0.4;
PSO momentum or inertia	w =0.9;

These PI parameter values are applied for four tank system of the laboratory set up. The controller parameter values are tabulated in Table 2 for Decentralized, GA and PSO based PI. Figure 6 and 7 shows that the variation of the fitness function with number of generations using GA and PSO based PI.

TABLE 2
CONTROLLER PARAMETERS

Type of Controller	**Controller parameters**			
	K_1	**K_2**	**K_{i1}**	**K_{i2}**
Decentralized PI	5.248	5.084	0.1235	0.0913
GA based PI	21.69	19.21	0. 52	0.35
PSO based PI	9.73	24.03	0.14	0.2

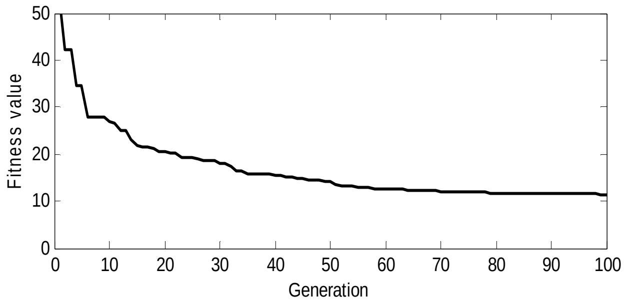

Figure. 6. Iteration Graph for GA

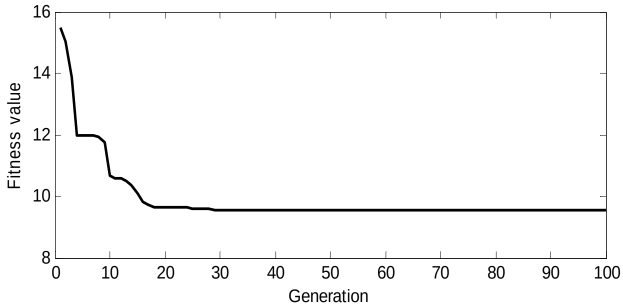

Figure. 7. Iteration Graph for PSO

IV. RESULTS AND DISCUSSION

Experimental results are carried out to evaluate the proposed control method by utilizing the LabVIEW software. The performance of the different control strategies are compared based on the ISE and the Integral Absolute Error (IAE) for the two controlled outputs h_1 and h_2. The design of the disturbance is also satisfactory for characterizing the performance of the three different control strategies.

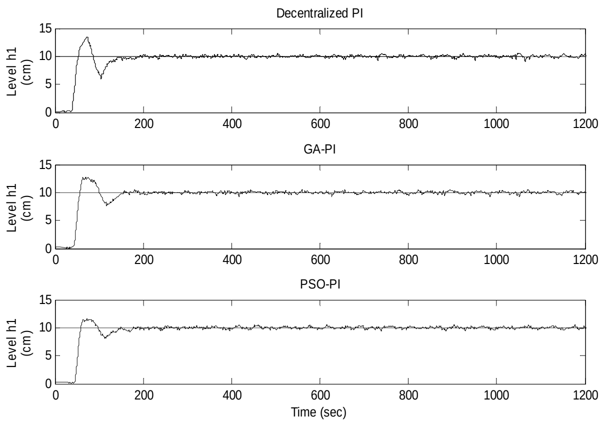

Figure 8. Experimental results for Closed Loop response of level h_1

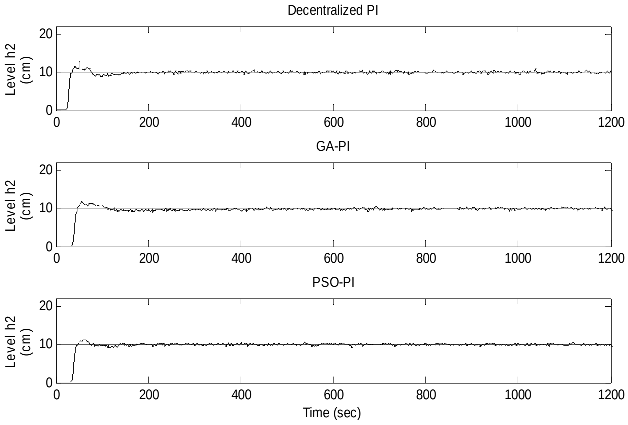

Figure 9. Experimental results for Closed Loop response level h_2

Figure 8 and 9 shows the experimental results of the closed loop response of water level h_1 and h_2 for decentralized PI, tuning PI parameters using GA and PSO. The ISE and IAE values of PSO tuned PI is less for both water levels h_1 and h_2 when compared to decentralized PI and GA based PI and shown in Table 3.

In order to test the performance of the proposed design procedure of PSO controller, simulation was carried out for the servo and regulatory operations. The set point tracking responses of the water level of h_1 and h_2 for the above controllers are given in Figure 10 and 11. At 1200th sec the set point is changed from 10cm to 12cm and at 2400th sec the set point is decreased from 12cm to 10cm. After that the set point is increased to 16cm at 3600th sec, and the response is plotted.

TABLE 3
PERFORMANCE COMPARISION OF VARIOUS CONTROLLERS
(TANK 1 AND TANK 2)

Type of Controller	Level Output of Tank1 (h_1)		Level Output of Tank2 (h_2)	
	ISE	***IAE***	***ISE***	***IAE***
Decentralized PI	23.06	4.45	17.34	3.33
GA based PI	16.58	3.40	12.7	3
PSO based PI	14.92	3.32	11.6	2.6

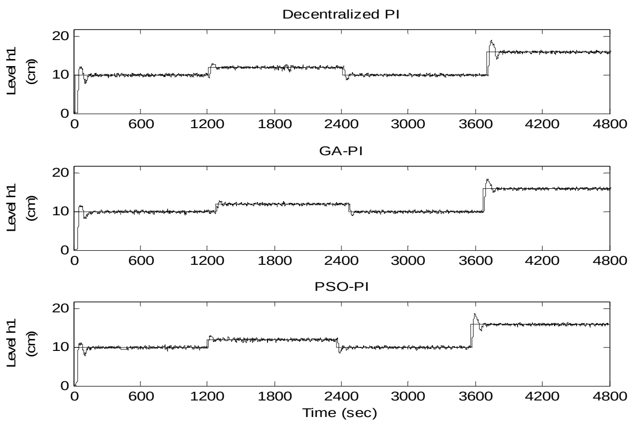

Figure 10. Experimental results for Set point tracking for the Responses of the water level (h_1)

The performance comparison of the set point tracking of the controllers for level h_1 and h_2 are given in Table 4 and 5 respectively.

TABLE 4
PERFORMANCE COMPARISION OF SETPOINT CHANGES (TANK 1)

Various set points		Type of Controllers		
		Decentralized PI	GA based PI	PSO based PI
Set point (10 cm)	ISE	25.5	18.1	16.5
	IAE	4.58	3.64	3.5
Set point (12 cm)	ISE	0.45	0.39	0.3
	IAE	0.73	0.72	0.59
Set point (10 cm)	ISE	0.23	0.29	0.2
	IAE	0.48	0.46	0.42
Set point (16 cm)	ISE	1.16	1.04	0.96
	IAE	0.82	0.52	0.48

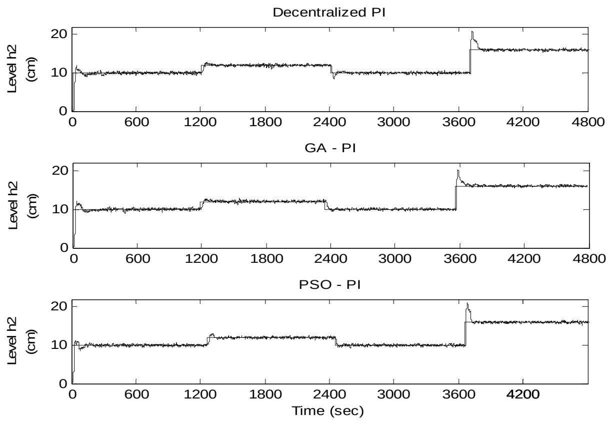

Figure 11. Experimental results for Set point tracking for the Responses of the water level (h_2)

TABLE 5
PERFORMANCE COMPARISION OF SETPOINT CHANGES (TANK 2)

Various set points		Type of Controllers		
		Decentralized PI	GA based PI	PSO based PI
Set point (10 cm)	ISE	25.5	13.9	12.6
	IAE	4.56	3.33	2.84
Set point (12 cm)	ISE	0.45	0.32	0.27
	IAE	0.73	0.61	0.56
Set point (10 cm)	ISE	0.23	0.23	0.19
	IAE	0.42	0.37	0.4
Set point (16 cm)	ISE	1.38	1.04	0.98
	IAE	0.55	0.52	0.4

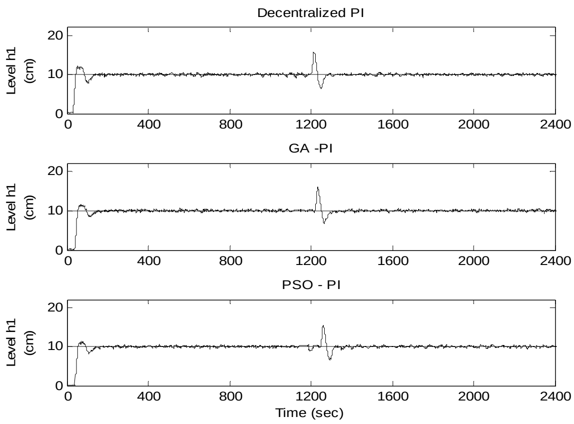

Figure 12. Experimental results for Regulatory response of water level h_1

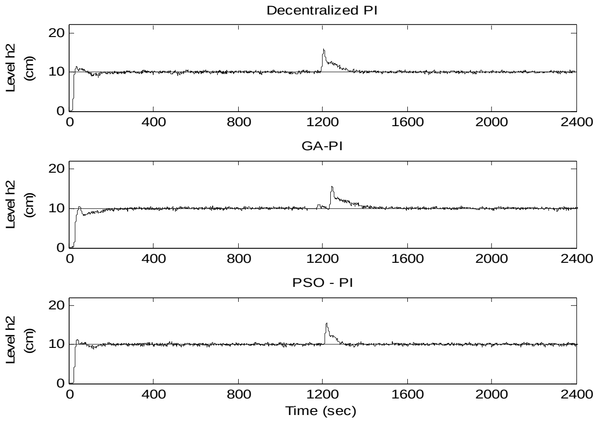

Figure 13. Experimental results for Regulatory response of water level h_2

Figure 12 and 13 are the regulatory responses of water level h_1 and h_2. Initially the level of tank 1 and tank 2 are maintained at steady state of 10cm. A sudden external disturbance (1000ml of water) is appended in tank 1 and tank 2 at 1200 sec. From the above response PSO responses settles quickly.

ISE and IAE values of regulatory response for all the controllers of both the levels are tabulated in Table 6. The system response of the level h_1 and h_2 (Fig. 10- 13) show both servo and regulatory operations.

TABLE 6
PERFORMANCE COMPARISION OF REGULATORY RESPONSE

Type of Controllers	**Regulatory Response (h_1)**		**Regulatory Response (h_2)**	
	ISE	**IAE**	**ISE**	**IAE**
Decentralized PI	11.46	3.02	11.81	3.29
GA based PI	11.34	2.87	11.18	2.56
PSO based PI	11.22	2.84	8.9	2.77

V. CONCLUSION

The performance/robustness comparison among the decentralized, GA and PSO controllers are designed to control the liquid level of the laboratory QTP. The PSO responses are compared with decentralized PI and GA responses. From these responses it is observed that the ISE and IAE values are low with PSO controller than with decentralized PI and GA controller. The results show that PSO controller performance is better and is robust for both servo and regulatory responses. The design of PSO controller is tested for an operating condition and the servo and regulatory responses are proved and established.The heading of the Acknowledgment section and the References section must not be numbered.

REFERENCES

[1] K.H.Johansson,"The Quadruple – Tank process: A multivariable laboratory process with an adjustable zero", IEEE Transactions on control systems technology, Vol.8, 3, pp 456-465, 2000.
[2] S.J.Shiu and S. H.Huang, "Sequential design method for multivariable decoupling and multiloop PID controllers", Industrial & Engineering Chemistry Research, Vol 37, pp 107–119,1998.
[3] W.Tan, J.Z. Liu and P. K. S.Tam, "PID tuning based on loop-shaping H_∞ control". IEE Proceedings on Control Theory and Applications, 145 (4), pp 485–490,1998.
[4] Q.G.Wang, Q.Zou, T.H.Lee and Q.Bi, "Autotuning of multivariable PID controllers from decentralized relay feedback", Automatica, 33, pp 319–330, 1997.
[5] M.Zhuang and D.P.Atherton, "PID controller design for a TITO system", IEE Proceedings on Control Theory and Applications, 141, pp 111–120, 1994.
[6] E.Shopova and N.Vaklievabancheva, "BASIC-A genetic algorithm for engineering problems solution", Computers & Chemical Engineering, Vol 30, 8, pp 1293-1309, 2006.
[7] R.Dimeo and K.Y. Lee, "Boiler-Turbine Control System Design Using a Genetic Algorithm", IEEE Transactions on Energy Conversion, December Vol. 10, 4, pp 752-759, 1995.
[8] C.L. Liu, J.Z. Liu, Y.G. Niu and D.L. Zeng, "Genetic algorithm-based multi-variables nonlinear boiler Model identification for 300mw power unit", Proceedings of the Second International Conference on Machine Learning and Cybernetics, Vol 1, pp 314-317, 2003.
[9] D Whitleya, T Starkweathera and C Bogarta, "Genetic algorithms and neural networks: optimizing connections and connectivity, parallel computing", Vol 4, 3, pp 347-361, 1990.

[10] D.E. Goldberg, "Genetic Algorithms in Search, Optimization, and Machine Learning", Addison-Wesley Publication, 1989.
[11] S.Y.Yuen, "A Genetic Algorithm that Adaptively Mutates and Never Revisits", IEEE Transactions on Evolutionary Computation, Vol. 13, 2, pp 454-472, 2009.
[12] Dongmei Zhang, Wei Liu, Ao Wang, and Qiao Deng, "Parameter Optimization for Support Vector Regression Based on Genetic Algorithm with Simplex Crossover Operator", Journal of Information & Computational Science, Vol.8, 6, pp 911-920, 2011.
[13] X.S.Yang, "Engineering Optimization, An Introduction with Metaheuristic Applications" Wiley 2010.
[14] S.Genovesi, R.Mittra, A.Monorchio and G. Manara, "Particle Swarm Optimization for the Design of Frequency Selective Surfaces", IEEE Transactions on Antennas and Wireless Propagation Letters, Vol. 5, pp 277-279, 2006.
[15] Y.Del Valle, G.K.Venayagamoorthy, S.Mohagheghi, J.C.Hernandez and R.G. Harley, "Partcle Swarm Optimization: Basic concepts, Variants and Applications in power systems", IEEE Transactions on Evolutionary computations, Vol 12, 2, pp 171-195, 2008.
[16] M.Sadeghierad, A.Darabi, H.Lesani and H.Monsef, "Optimal design of the generator of microturbine using genetic algorithm and PSO", International Journal of Electrical Power and Energy Systems, Vol 32, 2010, pp 804–808.
[17] Bouzid Mhamdi, Khaled Grayaa and Taoufik Aguili, "Hybrid of genetic algorithm with particle swarm optimization to shape reconstruction of perfect conducting cylinders", International Journal of Electronics and Communications, Vol 65, 2011, pp 1032-1039.
[18] Rakesh Malviya and Dilip Kumar Pratihar, "Tuning of neural networks using particle swarm optimization to model MIG welding process", Swarm and evolutionary computing, Vol 1, 4, pp 223-235, 2011.
[19] A.M. El-Zonkoly, "Optimal placement of multi-distributed generation units including different load models using particle swarm optimization", Swarm and evolutionary computing, Vol 1, 1, pp 50-59, 2011.
[20] B.Wayne Bequette, "Process control Modeling, Design and Simulation, Prentice Hall of India 2004.
[21] R.Venkata Rao, "Advanced Modeling and optimization of manufacturing process: International research and development", Springer series in advanced manufacturing, Springer, 2010.