International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 02 Issue: 01 | April 2015 www.irjet.net p-ISSN: 2395-0072

Design of Model Reference Adaptive Control based PI Controller for a Non-linear Spherical Tank System Using Particle Swarm Optimization

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Abstract - *This paper presents a Particle Swarm Optimization (PSO) based Model Reference Adaptive PI (MRA-PI) for a nonlinear Spherical Tank Level System(STLS). In this work Particle Swarm Optimization is adopted to find the optimized adaptation gain of MRA-PI controller. Minimization of Integral Absolute Error (IAE), peak overshoot (Mp) and settling time (ts) are chosen as the objective function. The performance of the proposed method is validated with a Conventional MRA-PI and Conventional PI controller. The simulation studies confirm that, the proposed method gives adequate performance in terms of error performance criteria.*

Key Words: STLS, MRA-PI, PSO based MRA-PI

1. INTRODUCTION

Chemical process presents many challenging control problems due to nonlinear dynamic behavior, uncertain and time varying parameters, unmeasured and frequent disturbances. Because of the inherent nonlinearity, most of the chemical process industries are in need of conventional control techniques. Spherical tanks find wide spread usage in gas plants. They are non-linear system because their area of cross-section keeps varying with the height of the tank. Therefore, Control of a spherical tank is important, because the change in shape gives rise to the nonlinearity.

Conventional controllers are widely used in industries since they are simple robust and familiar to the operator. The most basic and persistent controller algorithm used in the feedback control is proportional integral controller algorithm [1]. But due to the assumptions made, the PI controller settings usually do not cope up with non linear behavior of the process and are not capable to furnish the desired response at all operating points. To overcome this problem, an adaptive control techniques is implemented in non linear behavior system [2].

One of the popular and growing adaptive control method used in practical applications is model reference adaptive based PI (MRA-PI) Controller [3]. In order to get the optimal adaptation gain of MRA-PI, an intelligent soft computing auto tuning algorithm such as Fuzzy logic, Neural Network (NN), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO) are used [4]-[8]. The advantage of PSO algorithm is that, it is an auto tuning method, it does not require detailed mathematical description of the process and finds the optimal parameters based on the performance index provided for algorithm convergence. Although PSO has the characteristics of fast convergence, good robustness, easy implementation. In this work, the adaptation gains of MRA-PI controller is estimated using PSO and the simulations works are carried out.

2.MATHEMATICAL MODEL OF SPHERICAL TANK

The spherical tank level process model referred in Figure 1, in which the control input fin is the input flow rate (m3/s) and the output x is the fluid level (m) in the spherical tank. Let, r, d0 and x0 is the radius of spherical tank, thickness (diameter) of pipe (m) and initial liquid level height respectively.

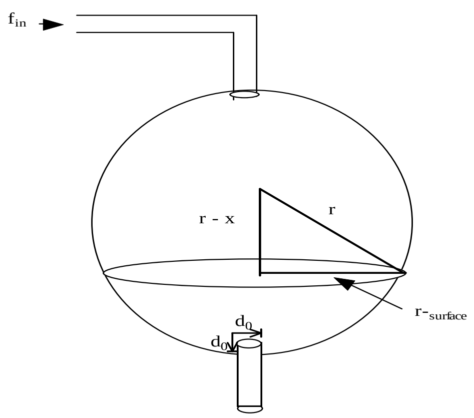

Fig.1 Spherical tank level process.

The Dynamic model [11] of the spherical tank is given by

$$\frac{dx}{dt} = \frac{f_{in}\,\delta t - \frac{\pi\, d_0^2}{4}\sqrt{2g\,(x - x_0)}}{\pi\,(2rx - x^2)}$$

3. IDENTIFICATION OF PI CONTROLLER PARAMETERS

The PI controller consists of proportional and integral term. The proportional term changes the controller output proportional to the current error value and the Integral term changes the controller output based on the past values of error. So, the controller attempts to minimize the error by adjusting the controller output.

The spherical tank level system is kept at a steady state of different operating point of 20%, 40%, 60% and 80%. A step size of 5% level for each operating point is applied and the variation of level against time for each operating point is recorded separately until a new steady state is attained. From the recorded data, the model parameters such as process gain (Kp) time constant (τp) and delay (td) are computed and tabulated in table 1. From the table, the worst case model parameters are considered for PI controller parameters.

Table.1 Identification of Worst case Model parameters

Operating Point (%)	Kp	τp	td
20	0.864	96.45	17.85
40	1.23	219	8
60	1.38	252.75	7.75
80	1.76	174.5	13.25

The identified worst case model is given by

$$P(s) = \frac{1.76}{96.45s+1} e^{-17.85s}$$

Table.2 PI controller parameter of STLS.

K_C	K_I
2.76	0.0464

4. Model Reference Adaptive PI (MRA-PI)

A tuning system of an adaptive control will sense these parametric variations and tune the controller parameters in order to compensate for it. The parametric variation may be due to the inherent non-linearity of the system such as Spherical tank Level System. In Model Reference Adaptive technique, a reference model describes the system's performance. The adaptive controller is then designed to force the system to behave like the reference model. Model output is compared to the actual output and the difference is used to adjust feedback controller parameters.

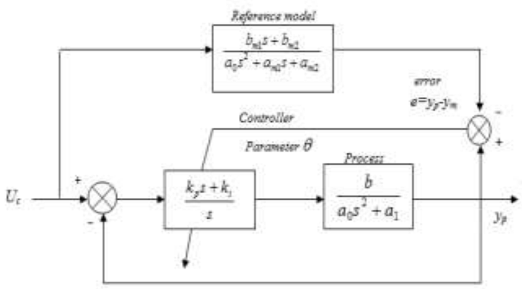

Fig.2. Block diagram of MRA_PI.

The Tracking error is given as,

$$e = y_p(t) - y_M(t)$$

$$\frac{d\theta}{dt} = -\gamma \frac{\partial J}{\partial \theta} = -\gamma e \frac{\partial e}{\partial \theta}$$

The cost function

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

where 'e' denotes the model error and 'θ' is the controller parameter vector. 'γ' denotes the adaptation gain. Instead of 'θ' the PI controller parameters K_P, Ki are considered.

$$K_p^* = \left(\frac{-\gamma_p}{s}\right) e \left(\frac{s}{a_0 s^2 + a_{M1} s + a_{M2}}\right) e$$

$$K_i^* = \left(\frac{-\gamma_i}{s}\right) e \left(\frac{1}{a_0 s^2 + a_{M1} s + a_{M2}}\right) e$$

5. Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995 [9], inspired by social behaviour of bird flocking or fish schooling. Every particle monitors its directions in the issue space which are related with the best arrangement (fitness) it has accomplished up until now. (The fitness value is also stored.) This value is called Personal Best (PBest). Another "best" value that is followed by the particle swarm enhancer is the best esteem, acquired so far by any particle in the neighbours of the particle. This area is called Local best (Lbest) at the point when a particle takes all the populace as its topological neighbours, the best value is a Global Best and is called GBest. The projected position of i^{th} particle of the swarm x_i, and the velocity of this particle v_i at $(t+1)^{th}$ iteration are defined and updated as the following two equations,

$$v_i^{t+1} = v_i^t + c_1 r_1 (P_i^t + x_i^t) + c_2 r_2 (g_i^t + x_i^t) \quad (19)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (1)$$

where i=1, ..., n and n is the size of the swarm, c_1 and c_2 are positive constants, r_1 and r_2 are random numbers which are uniformly distributed, determines the iteration number, p_i represents the best previous position (the position giving the best fitness value) of the i^{th} particle, and g represents the best particle among all the particles in the swarm. At the end of the iterations, the best position of the swarm will be the solution of the problem. It cannot be always possible to get an optimum result of the problem, but the obtained solution will be an optimal one [10].

Parameters used for PSO algorithm

The following parameters are chosen to obtain minimum Time domain criteria as a objective function.

The observation time Tob=25 Sec

The step size of the simulation Hs=0.001 Sec,

The average generations =130

The number of particles = 15

The range of λ and δ = 0 to 2.

The PSO setting parameters are c1=c2=1.5.

6. Results and Discussion

Performances of proposed controller are analyzed using step input at various level in the STLS. Initially the tank is maintained at 35 cm of operating level, after that, a step size of 5 cm of level is applied to control loop with PSO based MRA-PI control strategy. In the same way, test runs of conventional PI control values are carried out and their responses are presented in Figure.4. It is found that in PSO based MRA-PI makes the system to settle with minimum integral square error at all.

It is also clear that proposed controller tracks the set point quickly with minimum overshoot. The results prove that PSO based MRA-PI controller is appropriate for non linear process as it has least error values than the other controller strategies.

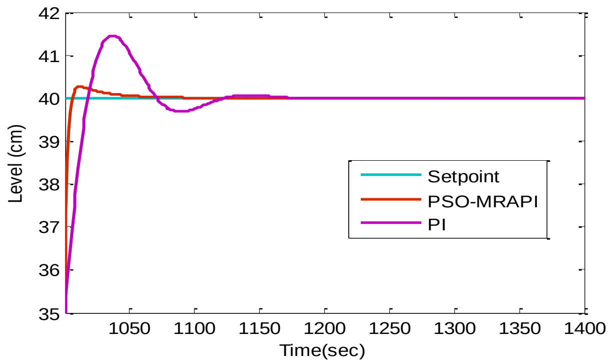

Figure.4. Servo response of STLS with PI and PSO MRA-PI at the operating point of 40.

Table.3. Performance Indices at different Operating range.

Controller	ISE	IAE
	Operating Point (35 to 40 cm)	Operating Point (35 to 40 cm)
PI	145.3	64.8
PSO based MRA-PI	21	15.1

6. Conclusion

In this paper, PSO based MRA-PI control strategy is developed and implemented for a spherical tank level system. This method is suitable for process control applications with a large delay, where a conventional PI controller yield a poor performance. The simulation results are furnished to illustrate the effectiveness of proposed controller with those of conventional PI control approaches. The performance indices are also proved that the proposed controller gives a superior performance than the existing control strategies.

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