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Review

Gain scheduled particle swarm optimization based internal model control for tank level system

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The proposed work attempts gain scheduled particle swarm optimization (PSO) based internal model control (IMC) for tank level process. IMC requires determining a single parameter λ, the filter constant. Optimal value of the filter constant is determined using PSO, an evolutionary technique. The tank process is nonlinear in nature. Model and inverse model are found for each linear region separately and clubbed together using a gain scheduler. The performance of the proposed controller shows the suitability of using it for the servo and regulatory control of nonlinear process.

Key words: Filter constant, gain scheduler, particle swarm optimization, internal model control.

INTRODUCTION

Control of liquid level plays a vital role in floatation plants. Level control is required in many industries like chemical industries, power plants, water treatment plants, etc. Although the Level process is nonlinear, but it is a self-regulating process reaching steady state for different input. During the past decades, the process control techniques have made great advance. Numerous control methods like adaptive control, neural control, fuzzy logic control, adaptive neuro fuzzy inference system (ANFIS) control has however, been developed. Still, proportional-integral-derivative (PID) controllers are considered as the workhorse of almost all the industrial process control applications due to their structural simplicity and robust performance in a wide range of operating condition as presented by JinKum (2004).

PID controller mainly depends on tuning of the gains, such as the proportional gain, integral time and the derivative time. Tuning the PID controller gains, play a major role in deciding the performance. Some literature provides many tuning methodologies. Tuning of PID parameters is based on the exact form of the process expressed by a transfer function (Krohling and Rey, 2001; Chwee (1988). Manufacturers and vendors use different tuning algorithms for designing the PID control parameters.

Model based control like the model predictive control; model reference adaptive control and dynamic matrix control are gaining popularity as stated by Santacesaria and Scattolini (1993) and Lee et al. (1999). But when there is a mismatch between the model and actual process, the closed-loop performance is also degraded; therefore, it is used rarely in industrial application. Qing and Gade (2001); Carcia and Morari (1982); Guan and Min-Sen (2001) and Aniruddha and James (1996) have worked on IMC which can be used in designing a controller and filter separately, based on the analysis of the control system's stability. This design can compensate for the mismatch between actual process and model with good robustness. IMC allows a transparent controller design procedure where control

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Figure 1. Hardware Set-up of Tank Level Process.

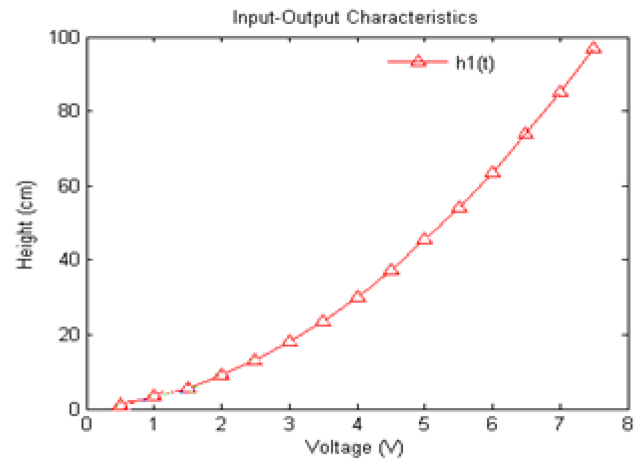

Figure 2. Voltage Vs. Height of the Tank.

quality and robustness are influenced in a direct manner.

The IMC concept, conceptualized by Brosilow (1996), Himer (2004) and Seborg (1989) approximates the feedback transfer function by Maclaurin's series designing the PID controller parameters. Here the tuning parameter is finding the filter time constant which plays a crucial role in deciding the performance of the output. Biological optimization algorithms such as evolutionary computing, swarm intelligence, and so on, were introduced to improve the optimization of parameters. At this point in time, Kennedy and Eberhart (1995) used the particle swarm optimization (PSO) for the search of optimal parameters.

Particle swarm optimization technique is an attractive method which gives an optimal global search. PSO designed and developed by Yoshida et al. (2007) and Mehdi et al. (2007) can be easily implemented; and it is computationally cheap because of its low memory and low speed requirements. It uses basic mathematical operators.

The crucial factor in internal model control, the filter constant, is tuned using PSO. Also, a gain scheduler is used to accommodate the complete nonlinear range. The gain scheduler requires an exogenous output and provides the controller gains. In the present work, gain scheduled PSO based IMC is proposed.

Process description

The setup diagram of the three interacting tanks is shown in Figure 1. The setup consists of cylindrical process tanks, overhead sump, submersible pump, differential pressure transmitter (DPT), rotameter and interfacing card. The process tank is cylindrical and made of a transparent glass.

Provisions for water inflow and outflow are made at the top and bottom of the tank respectively. A pump is used for discharging the liquid from the storage tank. The inflow to the tank is maintained by a variable speed pump.

DPT is used for liquid level measurement. In this open vessel process, tank pressure is given to the high-pressure side of the transmitter and the low-pressure side is vented to the atmosphere. A rotameter was used for monitoring of the level. A gate valve is provided at the outlet to maintain the level of water in the tank. Clockwise rotation ensures the closure of the valve, thus stopping the flow of liquid and vice versa.

A 25-pin male connector is used here to interface the hardware setup with the PC. The electrical output generated from the potentiometer is first converted into a digital value before applying it to the computer. The area of the tank is 615.7522cm^2 and the pump gain is 75cm^3/V.s.

Input-output characteristics

The tank process has a manipulated variable inflow to the tank (u) regulated by the control valve (Figure 2). The output of the process is the level (h) of the tank. The open loop response of the tank is obtained by varying the voltage u from 0.5V to 7.5V, Table 1.

Internal model control for tank level

Internal model controller involves a model based procedure where the process model is embedded in the controller. The IMC structure has a direct mode, an inverse model and a filter as shown in Figure 3. The model is determined by applying step input to the tank process for the five linear regions by the process reaction curve method. The inverse model is determined by inverting the model transfer function. The transfer

Table 1. I/O data obtained from the lab scale setup.

u1	h1	u1	h1
0.500	1.310	4.500	37.350
1.000	3.105	5.000	45.380
1.250	4.288	5.500	54.110
1.500	5.660	6.000	63.669
2.000	9.001	6.500	73.900
2.500	13.122	6.750	79.250
3.000	18.010	7.000	85.100
3.500	23.676	7.500	96.995
4.000	30.138	4.500	37.350

Table 2. Operating conditions of the tank.

Operating region	Operating range	Manipulated variable, u_0	Level of the tank, h_0
I region	0.5-2.0	1.25	4.288
II region	2.0-3.0	2.50	13.122
III region	3.0-5.0	4.00	30.138
IV region	5.0-6.0	5.50	54.110
V region	6.0-7.5	6.75	79.250

Table 3. Operating conditions of the tank.

Operating region	Model
I region	$\frac{3.426}{107s+1}$
II region	$\frac{5.248}{158s+1}$
III region	$\frac{7.5325}{232s+1}$
IV region	$\frac{9.8418}{305s+1}$
V region	$\frac{11.733}{367s+1}$

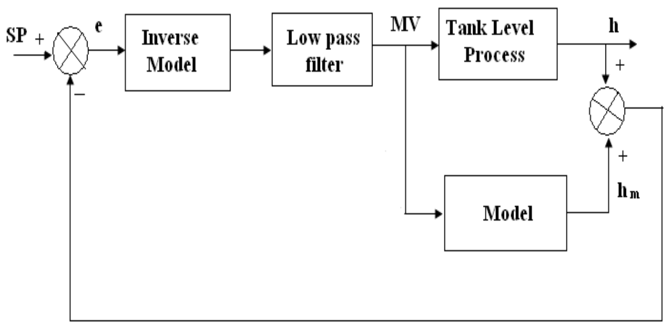

Figure 3. Block diagram of the modified IMC.

function model and the inverse model are shown in Tables 2 and 3. IMC involves a single tunable parameter, the filter constant. Variation in filter constant abruptly disturbs the performance of the process. An attempt has been made to design the filter constant using PSO technique.

Particle swarm optimization (PSO) technique

PSO algorithm is one of the optimization techniques and a kind of evolutionary computation technique. The method is found robust in solving problems featuring nonlinearity and non-differentiability, multiple optima and high dimensionality through adaptation derived from the social-psychological theory.

The basic PSO is developed from research on swarm such as fish schooling and bird flocking. The observation leads to the assumption that every information is shared inside flocking. Moreover, according to observation of behaviour of human groups, behaviour of each individual (agent) is also based on behaviourial patterns authorized by the groups such as customs and other behaviour patterns according to the experiences by each individual. The assumption is a basic concept of PSO (Mehdi et al., 2007). In the PSO algorithm instead of using evolutionary operators such as mutation and crossover, to manipulate algorithms, for a d-variabled optimization problem, a flock of particles are put into the d-dimensional search space with randomly chosen velocities and positions knowing their best values so far (Pbest) and the position in the d-dimensional space. The velocity of each particle, adjusted according to its own flying experience and the other particle's flying experience. For example, the ith particle is represented as $\varkappa_i = (\varkappa_{i,1}\ \varkappa_{i,2},\ldots,\varkappa_{i,d})$ in the d-dimensional space. The best previous position of the ith particle is recoded and represented as $Pbest_i = (Pbest_{i,1}\ Pbest_{i,2},\ldots, Pbest_{i,d})$
The index of best particle among all of the particles in the group is $gbest_d$. The velocity for particle i is represented as $\upsilon_i = (\upsilon_{i,1}\ \upsilon_{i,2},\ldots, \upsilon_{i,d})$. The modified velocity and position of each particle can be calculated using the current velocity and the distance from $Pbest_{i,d}$ to $gbest_{i,d}$ as shown in the following formulas:

$$\upsilon_{i,m}^{(t+1)} = w.\upsilon_{i,m}^{(t)} + c_1 * rand()* (pbest_{i,m} - \varkappa_{i,m}^{(t)}) + c_2 * rand()* (gbest_{i,m} - \varkappa_{i,m}^{(t)})$$

$$\varkappa_{i,m}^{(t+1)} = \varkappa_{i,m}^{(t)} + \upsilon_{i,m}^{(t+1)}$$

i = 1,2,….,n
m = 1,2,….,d
where:
n :Number of particles in the group
d :dimension

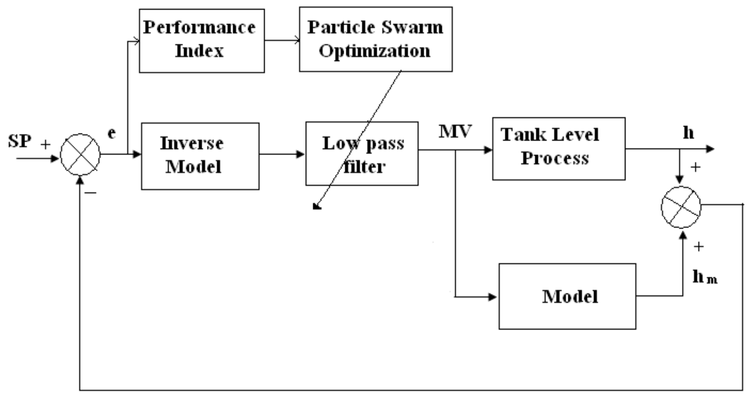

Figure 4. Block diagram of the PSO optimized IMC for the tank level control.

i :Pointer of iterations(generations)
$\upsilon_{i,m}^{(t+1)}$:Velocity of particle I at iteration t
$V_d^{min} \leq \upsilon_{i,d}^{(t)} \leq V_d^{max}$
w :Inertia weight factor
c_1,c_2: Accelration constant
rand() :Random number between 0 and 1
$\varkappa_{i,d}^{(t)}$: Current position of particle I at iterations
$pbest_i$:Best previous position of the i^{th} particle
gbest: Best particle among all the particles in the population

Online tuning of filter constant λ using PSO

The single tunable parameter in the internal model control, λ is tuned using the PSO. In this paper, a PID controller tuned using the PSO based IMC was developed. The PSO algorithm was mainly utilized to determine the optimal filter constant which in turn is used to tune the PID controller parameters. The technique of particle swarm optimization is proposed as a means of tuning lambda which in turn generates the PID controller parameters. The technique uses PSO to tune the λ online for a minimum ISE for each region, separately. Minimizing the following error criteria generates the controller parameter:

$$ISE = \int_0^T [r(t) - y(t)]^2 dt$$

Where: r(t) = reference input, Y(t) = measured variable. At first, the particle position, that is, the λ value is randomly initialized. The p_{best} and g_{best} are determined by the fitness function based on the inverse of the error criteria, ISE. The fitness function is defined as 1/(1+ISE). The smaller the value of the fitness function, the better the performance of the system response with the specified PID parameters. Thus, the next movement for each particle can be computed by updating the velocity and position vector. After the required number of iteration, the optimized λ value is decided. The number of iteration of the process simulation is considered as 30 with inertia of 1.0. The correction factor c_1 is considered as 2.0 and c_2 as 3.0 with a swarm size of 25. Figure 4 shows the block diagram for online tuning of λ using PSO for the IMC, λ is chosen as 0.6268.

Gain scheduled IMC based control of tank

The process model and the inverse model were selected depending on the operating condition. The Gain scheduler is used to accommodate the complete operating conditions. Figure 5 shows the servo control of the tank process with set point change in every 3000^{th} sampling instant. Figure 6 shows the regulatory response of the process with disturbance of magnitude -3.7, 4.7, 5.7 and -3.7 added to the process output externally by the software. Figure 7 shows the servo-regulatory response of the tank level setup with servo change applied every 5000^{th} sampling instant and disturbance applied at 2500^{th} sampling instants. From the responses of Figures 5,6 and 7, it is clear that the proposed control scheme is capable of tracking the set point and rejecting the disturbance.

Conclusion

This paper proposes a novel idea for the optimal design of the IMC controller globally optimized using PSO. The entire region is accommodated by the gain scheduler. From the response it is clear that the proposed controller is capable of tracking the set point accurately. The disturbance rejection is also excellent. The servo

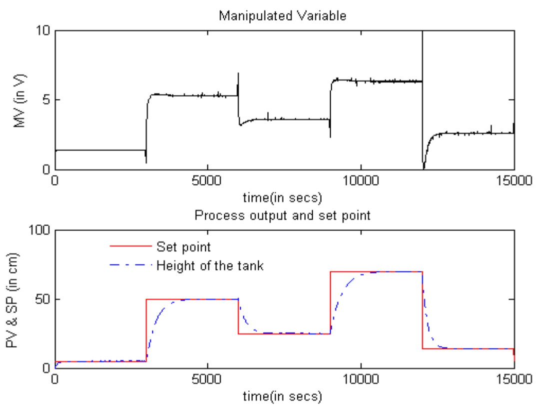

Figure 5. Servo control of tank level process.

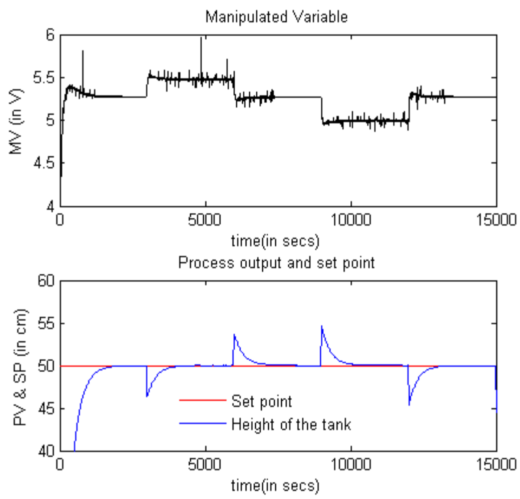

Figure 6. Regulatory response of tank level process.

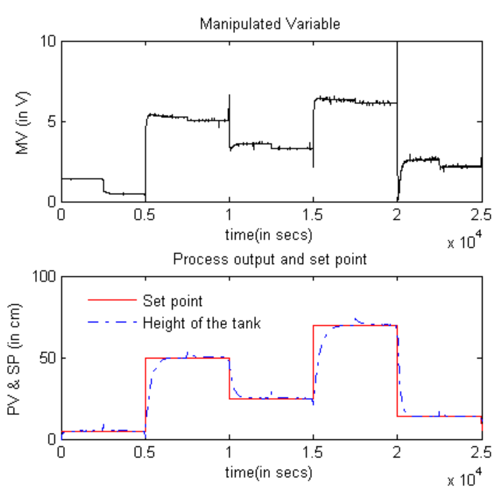

Figure 7. Servo-regulatory control of tank Level process.

regulatory response makes it clear that the proposed controller can be a viable solution for any nonlinear process.

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