PERFORMANCE ANALYSISOF LAG DOMINATED SYSTEM

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ABSTRACT

Gravity Drained Tank System is a Bench mark system and the response for it has been already taken by using Conventional Controllers (LADRC, IMC , AMIGO, SIMC). Now in this project we are going to check and find the response of Gravity Drained Tank System by using Heuristic method (PSO).The conventional controllers contains proportional (P), integral (I), derivative (D), proportional -integral (PI), proportional -derivative (PD) and proportional-integral-derivative (PID) controllers. It is used in the forward path of the system. Conventional controllers are used in creativity, rules of thumb, selection and training of executives.The main advantage of adopting a heuristic approach is that it offers a quick solution, which is easy to understand and implement. Heuristic algorithms are practical, serving as fast and feasible short-term solutions to planning and scheduling problems. Heuristic problem solving techniques applied to training human decision makers and constructing heuristic computer programs. It is an optimization technique it is successfully used in many different engineering fields also. The method can be interpreted as a stochastic damped mass-spring system. This analogy served us to show the PSO continuous model and to deduce a of PSO algorithms rising from the discretization of the PSO continuous model. So, we can analyze their respective first order and second order stability regions from the stochastic point of view.

Keyword: *Lag-Dominated, Particle Swarm Optimization, Velocity Update, Position Update, Inertia Weight.*

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1. INTRODUCTION

Controller design is major research areas in the field of process control and allied areas. In order to design a controller, it is important to develop an approximated process model around the operating region. Finding of dynamic transfer function models from experimental data is essential for model based controller design. Often derivation of rigorous models is difficult due to complex nature of system under control. Normally, tuning of controllers to stabilize a system and impart adequate disturbance rejection is critical. Based on operating regions, most of the systems exhibit stable and/or unstable steady states. Many real time process loops are inherently complex by design. Consequently, there has been much focus in the literature on tuning the industrially standard PID controllers for complex systems.

System identification is necessary to design and implement a model based controller. Identification is a preliminary practice to develop mathematical models of a process from experimental data. Identification procedure followed for stable system is uncomplicated and a simple open loop test is sufficient to develop an approximated model around the operating region. For complex systems, the identification procedure has to be performed in closed loop condition.

In control system literature, PID and modified forms of PID controllers are still widely used because of their structural simplicity, reputation and easy implementation, despite the significant developments in newly process control schemes such as model predictive control, Internal Model Control (IMC), and sliding mode control (Vijayanand Panda 2012). Onbased studies of many models on fine tuning the PID controllers have provided insight for better understanding of the controller performance for stable and unstable process models. For most of the stable systems, two degree of freedom PID controller offers a viable result for both the reference tracking and disturbance rejection. For unstable systems, the conventional PID controller offers satisfactory results when θ/τ ratio is < 0.5. When complexity of the process model increases, (systems with larger θ/τ ratio, system with integrator, systems with multiple unstable poles, and systems with a right-half plane zeros) conventional PID controller results in large overshoot and large settling time.

The conventional PID tuning methods discussed by most of the researchers for complex systems are purely based on an approximated first or second order model with a time delay. The tuning procedure employed for one particular model could not provide a satisfactory response for other process models. Thus, in recent years, heuristic algorithm based model free controller design is adopted by the researchers.

2. LITERATURE SURVEY

TITLE**: Tunable Method of PID Controller for Cascade Control System**

AUTHOR: R. Angel Sujitha, L. R. Swathika and V. Vijayan

YEAR: 2019

JOURNAL: Journal of Adv Research in Dynamical & Control Systems, Vol. 11,04-Special Issue.

TITLE**: Optimal H2 IMC-PID controller with set-point weighting for integrating processes**

AUTHOR: V. Supraja and V. Vijayan

YEAR:2018

JOURNAL:Int. J. Pure Appl. Math., vol. 118, no. 11, pp. 195–198.

TITLE**: Design of PID Controller with Compensator using Direct Synthesis Method for Unstable System**

AUTHOR: G. Atchaya, P. Deepa, V. Vijayan, and R. C. Panda

YEAR: 2016

JOURNAL: Int. J. Eng. Comput. Sci., vol. 5, no. 4, pp. 16202–16206.

TITLE**: Modified parallel cascade control strategy for stable, unstable and integrating processes**

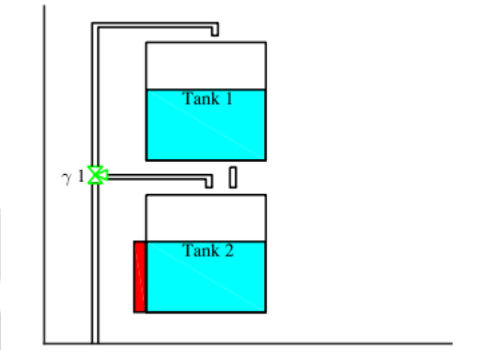
AUTHOR :Raja, G.L.; and Ali, A.

YEAR:2016

JOURNAL: ISA Transactions,65,394–406.

3. PROCESS

The gravity drained tanks process, as shown in the below figure, is comprised of two tanks stacked one above the other. The inlet flow rate giving the upper tank is changed by a pump output, while the liquid drains freely through the bottom of the upper tank to the lower tank in here. The liquid is getting drains freely through the bottom of the lower tank to a pool, where the pump is taking the liquid. The main aim is to adjust the pump output to maintain the liquid level in the lower tank at set point. The position of value acts as a disturbance to this gravity drained.



The gravity drained tanks process

At the initial stage, the system was approximated by FOPDT model, which is required for proposed tuning rules. Based on the obtained open loop experimental data from the output of pump to the lower tank of liquid level, the FOPDT parameters are obtained as $k = 0.202$, $T = 97.4$, $\tau = 15.6$. Then according to the (39) the parameters of LADRC were chosen as: $\omega c = 0.2493$, $\omega o = 0.1135$, $b = 0.000897$ and $\lambda = 1$. The control performance of the tuning rules is illustrated in Fig. 13(a). For comparing the above, the relative the lower tank of liquid level controlled by IMC-PID and SIMC-PID. It is concluded that, LADRC with the proposed tuning rules is more stable and the obtained response much faster than SIMC-PID. In adding to that, the pump output of this LADRC is smoother than IMC-PID.

The benchmark system on which we are working is a gravity drained system[28]. Transfer function of the above system.

$$P(s) = \frac{k}{Ts + 1} e^{-\tau s}$$

k – Gain value taken as 1

T – Time Constant value taken as 10

τ - value taken as 1

Kp, Ki, Kd values :

S.NO	Kp	Ki	Kd
PSO	13.2639	1.9263	1.7075
LADRC	0.638	0.1648	0.9863
IMC	8.32	0.8	3.2198
SIMC	5	1	0
AMIGO	4.7	1.119	2.279

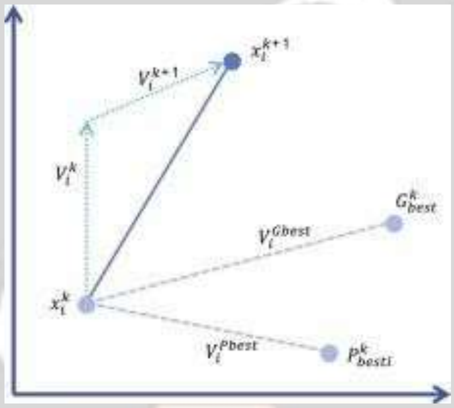
PARTICLE SWARM OPTIMIZATION

The PSO algorithm emulates the interaction to the share information between members. It has been applied in numerous field in optimization and in combination with other existing algorithms. Through agents, this method performs the search of the optimal solution, also known as particles, whose trajectories are adjusted by a stochastic and a deterministic component. Every particle is being influenced by the group's 'best' position and its 'best' achieved position, but moves randomly. A particle is defined by its velocity vector, v_i and position vector, x_i. Here each iteration, belongs to the new velocity and every particle changes its position:

vit+1=ωvit +c1r1(xBestit−xit)+c2r2(gBestit−xi) xit+1=xit+vit·t

here xBest and gBest denotes the best particle position and best group position and the parameters ω, c_1, c_2, r_1 and r_2 are respectively weight of inertia, two positive constants and two random parameters within [0, 1]. In the baseline PSO unit is chosen as ω, but an improvement of the algorithm is found in its implementation inertial using ω ≈ [0.5 0.9]. Usually the values of the minimum and maximum velocity are defined and initially the particles are distributed randomly to find in every possible locations.

The mainadvantages of PSO over other derivative-free methods is the decreased number of parameters to tune and constraints acceptance. The below figure illustrates a 2-D representation of one particle, 'i', movement between two positions. But the properties of the algorithm allow for solution variable to guarantee space exploitation of solution.



The study highlights simulated annealing and particle swarm optimization as the good compromise, where particle swarm optimization presented a better solution. PSO was also executed bychenetal. To frequently optimize the energy management and design of a parallel hybrid electric vehicle with interest in both reduction of emissions and consumption of fuel.

The authors claimed a substantial reduction of fuel and emitthe exhaust emissions by combining design and control with particle swarm optimization. PSO was found in the year 1995 by Kennedy and Eberhart [6] based on social activities in flock of birds and school of fish. Because of its adaptability and dominance, this method was used to find the global optimum solution in a complex search space during the control design problems. It is few dependent of a set of initial points than other optimization method. PSO is a derivative free algorithm. The PSO algorithm has two conventional equations such as velocity update and position update as given below [7-10];

$$V_i(t+1)=W^t.V_i^t+C_1R_1(P_i^t-S_i^t)+C_2R_2(G_i^t-S_i^t) \quad (3.1)$$

$$X_i(t+1)=X_i^t+V_i(t+1) \quad (3.2)$$

Here W^t is inertia weight assigned as 0.75, V_i^t is the current velocity of particle, $V_i(t+1)$-updated velocity of particle , X_i^t-current position of particle, $X_i(t+1)$-updated position of particle, R_1, R_2 are the random numbers [0,1] and C_1 and C_2=2.1.

PSO FLOW CHART

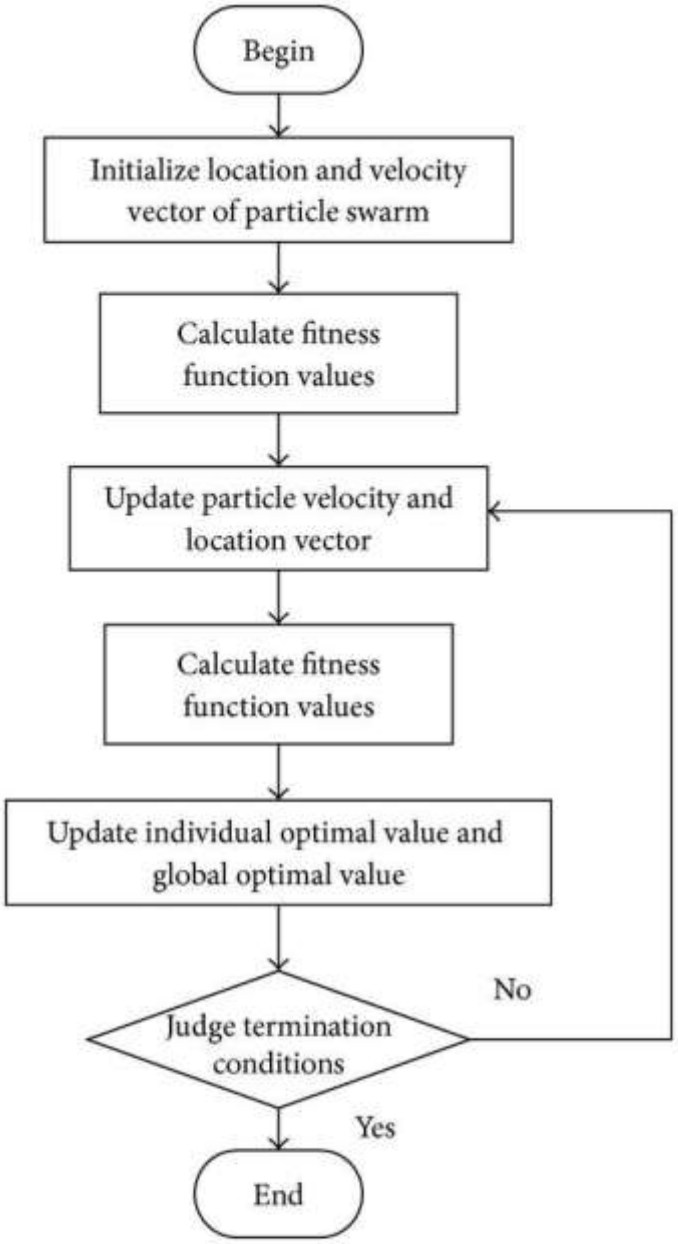


Figure5.7 Flowchart of PSO

The prior works of Particle Swarm Optimization (PSO) mostly applied to a wide range of engineering optimization problems, including path finding, scheduling, object recognition, face detection, and other application areas. PSO also provides a new way for industrial process identification and controller design.

Jain and Nigam (2008) proposed a PD-PI controller design for a highly nonlinear inverted pendulum system using PSO algorithm. The effectiveness of the method is validated through a comparative study with GA. Zamani et al (2009) discussed about PSO based H_α PID controller design for Single Input Single Output (SISO) and Multi Input Multi Output (MIMO) process models. A novel weighted sum of multiple objective function is developed using the frequency domain specifications, time domain specifications and the error. The superiority of the proposed method is validated with GA and simulated annealing algorithms. Zamani et al (2009a) designed a fractional order PID controller for an Automatic Voltage Regulator (AVR) system using PSO, and better robustness is achieved for the system with model uncertainties. Chang and Shih (2010) developed an improved PSO algorithm to design an optimal PID controller for reference tracking problem of a nonlinear inverted pendulum system. In this algorithm, a third learning parameter C_3 is introduced into the original velocity updating formula inorder to enhance the optimization search ability of basic PSO which results in improved convergence compared to existing PSO.

Kanthaswamyand Jovitha (2011) proposed procedure, simple derivative search and implicit filtering based on hybrid PSO algorithm. With simulation study, it is conformed that, proposed method provides improved convergence compared to original PSO. The method is tested and validated on a class of stable and unstable systems. Pillay and Govender (2011) proposed PSO based on setpoint weighted PID controller tuning for a class of unstable First Order Plus TimeDelay systems. Minimization of Integral Time Absolute Error (ITAE) is prioritised as the performance index, and it provides a good response when compared to existing classical tuning procedure.

An adaptive PSO algorithm to estimate the model parameters for a class of nonlinear systems in both offline and online methods was proposed by Modares et al. The accuracy and search speed of the proposed adaptive PSO is confirmed with linearly decreasing inertia weight PSO, dynamic inertia weight PSO, nonlinear inertia weight PSO, and GA. An adaptive PSO based system identification and control procedure for stable and discrete nonlinear systems was discussed by GA. Alfi and Modares In system identification procedure, the structure of a system is assumed to be known previously, and the algorithm is allowed to search the system parameters in D dimensional search space. The identified model is then considered to design an optimal PID controller. The method achieves faster convergence speed and better solution accuracy with minimum incremental computational burden compared to PSO algorithm with linearly decreasing inertia weight and GA. Alfi (2011) discussed an adaptive PSO algorithm to estimate the parameters of a class of nonlinear systems. Initially, search ability of the proposed algorithm is tested with benchmark functions such as Griewank, Rosenbrock and Rastrigrin function. The weighted sum of error function is chosen as the objective function to identify the global optimal values.

Alfi (2012) implemented PSO algorithm in identification of parameters of Lorenz chaotic system. A dynamic inertia weight is assigned for the PSO algorithm, to cope with the online system parameter identification problem. Inorder to increase the search efficiency and convergence rate, the inertia weight for every particle is dynamically updated based on the feedback taken from the fitness of the best previous position found by the particle. The performance of the discussed method is validated with real coded genetic algorithm.

TUNNING PROCEDURE OF PSO

The implementation of PSO has the following steps.

Step 1 *(initialization of swarm).* The particles are randomly generated between the minimum and maximum limits of parameter values for a population size

Step 2 *(evaluation of objective function).* For algorithm convergence objective function values of particles are valuated using the performance criteria for algorithm convergence.

Step 3 *(initialization of pbest and gbest)* Set as the initial *pbest*values of particles the objective values obtained above for the initial particles of swarm Set as the initial *pbest*values of particles. The best value among all the *pbest*values is identified as *gbest.*

Step 4 *(evaluation of velocity).*For each particle new velocity is computed using (5).

Step 5 *(update the swarm).*The position of particle is updated using (6). The objective value function are calculated for updated positions of particles. If the new value is good than the previous *pbest*, the new value is set to *pbest*. Similarly, *gbest*value is also updated as the best *pbest.*

Step 6 *(stopping criteria).* If the stopping criteria are met, particles position represented by *pbest*are the optimal values. Or, the above told procedure is again repeated from Step 4 until the specified iteration is completed.

4.RESULTS AND DISCUSSION

CLOSED LOOP RESPONSE

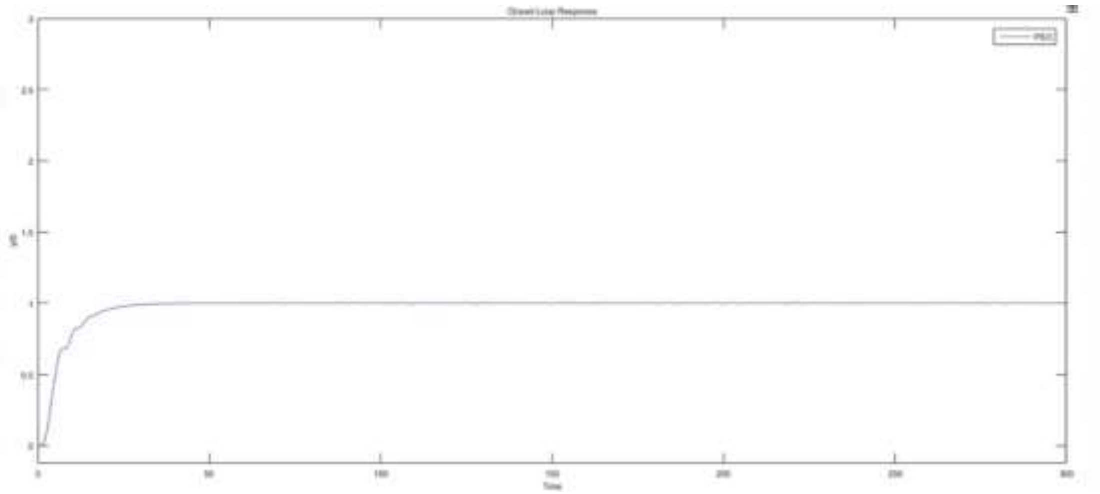


Fig. Closed Loop Response of PSO

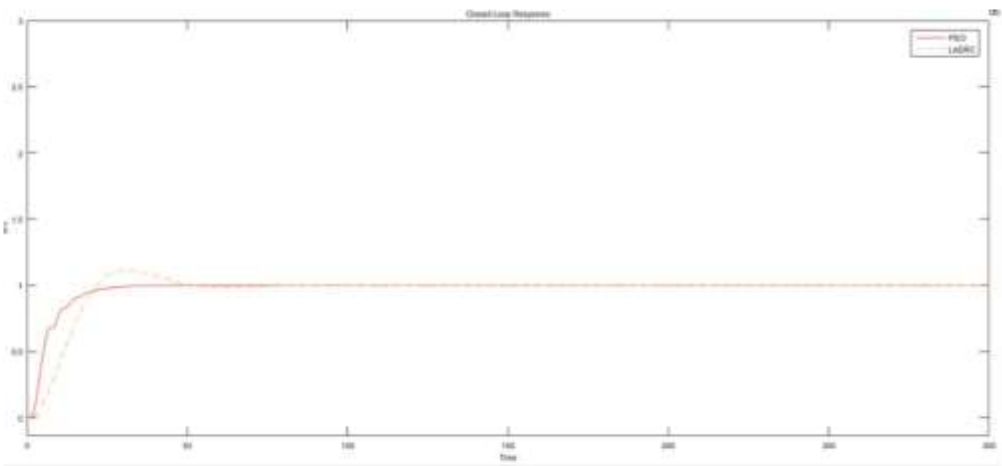


Fig.Closed Loop Response of PSO VS LADRC.

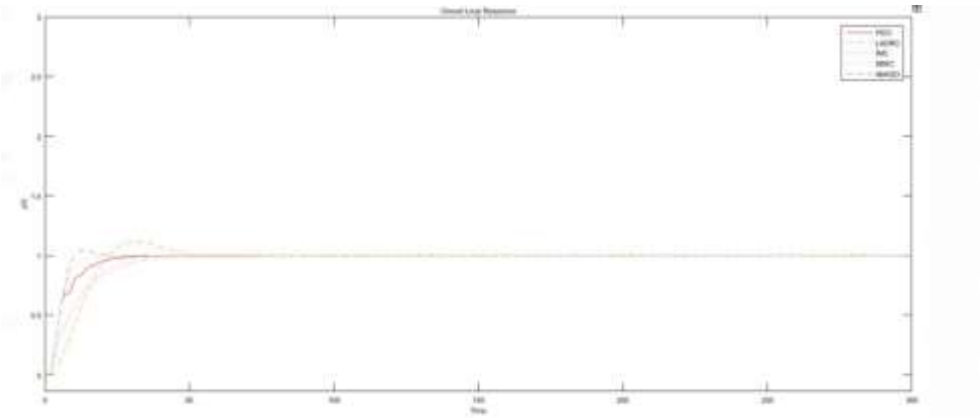


Fig. Closed Loop Response of PSO, LADRC, IMC, SIMC, AMIGO.

REGULATORY RESPONSE

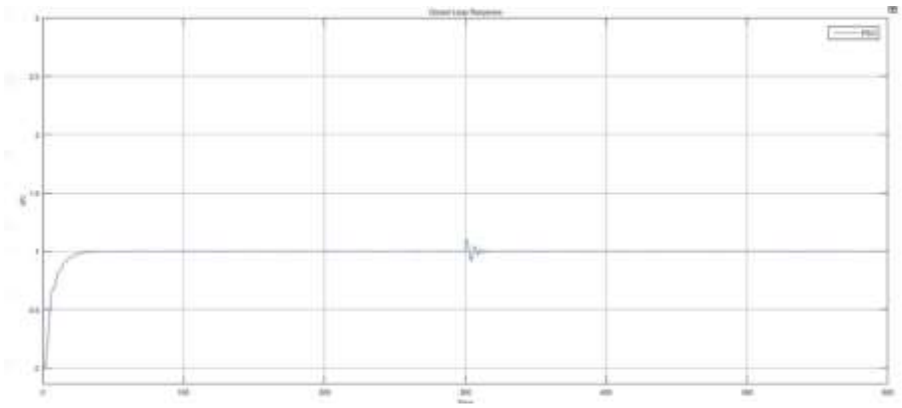


Fig. Regulatory Response of PSO.

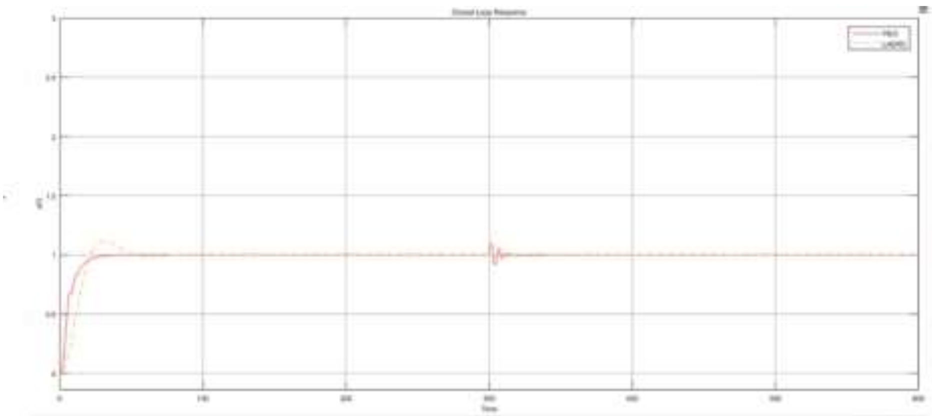


Fig. Regulatory Response of PSO VS LADRC.

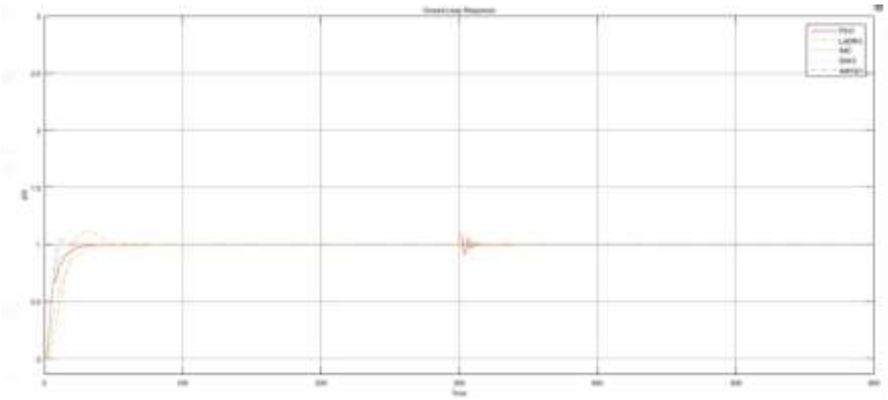


Fig. Regulatory Response of PSO, LADRC, IMC, SIMC, AMIGO.

SERVO RESPONSE

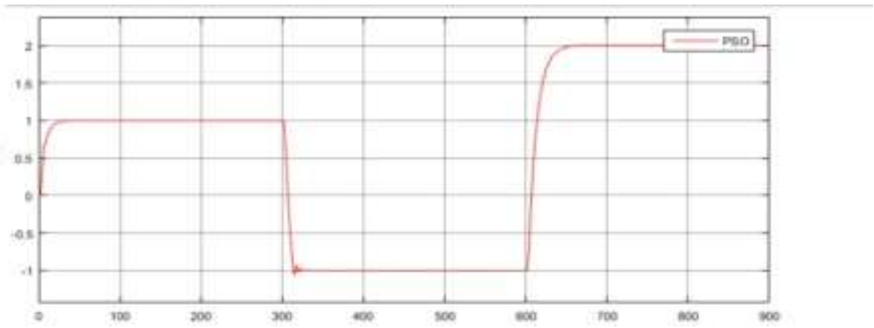


Fig. Servo Response of PSO.

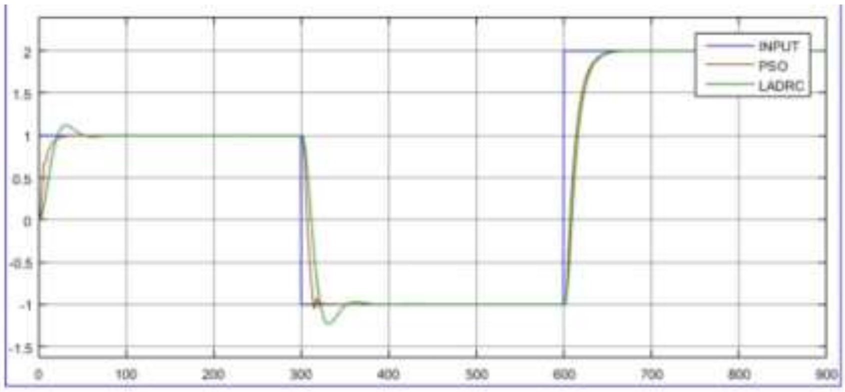


Fig.Servo Response of PSO VS LADRC.

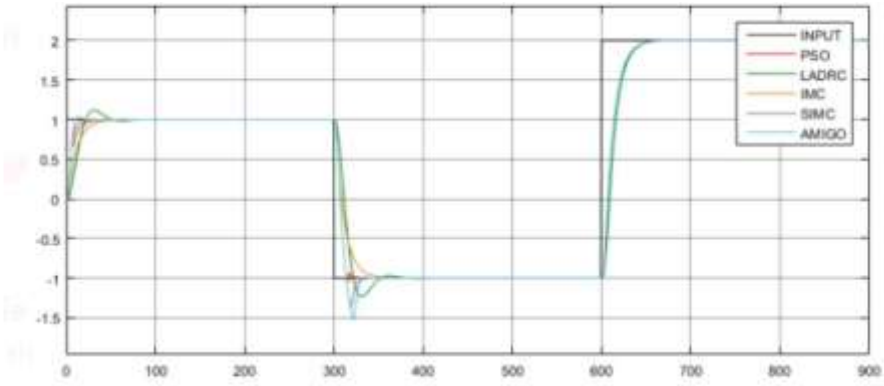


Fig. Servo Response of PSO, LADRC, IMC, SIMC, AMIGO.

COMPARISON:

Controllers	Settling Time (sec)	Rise Time (sec)	Peak Time (sec)	Peak Overshoot(%)
PSO	74.5	38.110		
LADRC	91.294	21.917	1.118	11.8%
IMC	72.45	70.69		
SIMC	66.7	26.189		
AMIGO	67.71	10.332	1.008	0.8%

Error Comparison of Regulatory Response:

Controllers	ISE	IAE
PSO	4.547	7.971
LADRC	14.81	9.038
IMC	11.91	6.66
SIMC	6.351	8.031
AMIGO	6.005	7.996

Error Comparison of Servo Response:

Controllers	ISE	IAE
PSO	96.84	60.74
LADRC	129.5	85.75
IMC	104	73.28
SIMC	97.15	61.71
AMIGO	98.14	63.31

4.CONCLUSION

Heuristic controller is better than conventional controller, because error of ISE, IAE in Heuristic Controller is lesser when compared to error of ISE, IAE in Conventional Controller. In this paper, heuristic algorithm based design methods aims to enhancing PID control complex Multi Input Multi Output process is implemented. It is shown graphically that there is a substantial improvement in time domain specification in terms of lower overshoot and less error index in PSO based PID controller. From the results, the designed PID controllers using PSO based optimization have less overshoot compared to that of the rest of the optimization methods. Furthermore, the PSO based PID controllers which are optimized with different performance indices like ISE, ITSE, IAE and ITAE have better performances, than the other controllers. Therefore the benefit of using a heuristic optimization approach is observed as a complement solution to improve the performance of the PID controller. Yes, PSO is one of the recent and efficient optimization tools there are many methods can be used as the optimization tools.

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