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Comparison of PID controllers with PSO and ACO for isothermal process (CSTR)

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Abstract

An isothermal chemical reactor (CSTR) is a common ideal reactor type in chemical engineering. The major goal of industries is to analyse dynamic chemical processes and develop automatic control strategies to operate them safely and economically. PID controllers are simple versatile feedback compensator. PID controllers are often the solution of choice when the controller is needed to close the loop. Swarm intelligence (SI) a derivative of CI, describes the collective behaviour of decentralized, self-organized systems. Particle Swarm Optimization (PSO) is a relatively new technique, for optimization of continuous non-linear functions. It was first presented in 1995 by James Kennedy and Eberhart. This paper clearly confers the comparison of traditional tuning techniques with Particle Swarm Optimization and Ant Colony Optimization. Performance index (ISE, ITAE, IAE, and MSE) and time domain analysis are calculated to prove that PSO is the best method for optimization comparing to other methods.

Keywords: Particle swarm optimization, Ant colony optimization, ZN (Ziegler-Nichols), TL (Tyreus-Luyben), CSTR (continuous stirred tank reactor).

1. Introduction

These are the most basic of the continuous reactors used in chemical processes. The continuous flow stirred tank reactor is also known as vat- or back mix reactor. Continuous stirred-tank reactors (CSTRs) are open systems, where material is free to enter or exit the system that operates on a steady-state basis, where the conditions in the reactor don't change with time. Reactants are continuously introduced into the reactor, while products are continuously removed. Continuous stirred-tank reactors are most commonly used in industrial processing, primarily in homogeneous liquid-phase flow reactions, where constant agitation is required. They may be used by themselves, in series, or in a battery.

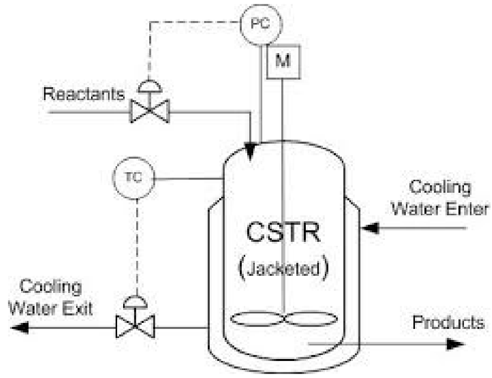

Figure 1: cross sectional diagram of CSTR

The reactant conversion in a chemical reactor is a function of the residence time or its inverse, the space velocity. For an isothermal CSTR, the product concentration can be controlled by manipulating the feed flow rate, which changes the residence time(for a constant volume reactor).

We consider a series-parallel reaction of the following form(known as the van de vusse reaction scheme):

$$A \rightarrow B \rightarrow C$$

$$2A \rightarrow D$$

The desired product is component B, the intermediate component in the series reaction. The reaction scheme is:

A=Cyclopentadiene, B=Cyclopentenol, C=Cyclopentanediol, D=Dicyclopentadiene.

PID controllers are widely used in industries.

An ideal PID controller is described by the control law

$$c(t) = k_p e(t) + k_i \int_0^t e(t)dt + k_d \frac{d}{dt} e(t)$$

Kp = Proportional gain

Ki = Integral gain (Kp /τi)

Kd = Derivative gain (Kp *τd)

C(t) = Controlling signal.

e(t) = error signal with respect to time

This is not physically realizable because no instrument can take a perfect derivative. It eliminates offset, provides fast response. PID controllers are used in process industry to control slow variables such as temperature, pH and other analytical variables.

Tuning a PID controller means setting the proportional, integral and derivative constant to get the best possible control for a particular process. Adjusting the controller gains, to satisfy the performance specifications like margin of stability, transient response and bandwidth, improves the system robustness. The performance of the tuned controller can be represented as a function of error for quantitative analysis. The commonly employed performance indices are Integral Absolute Error, Integral Squared Errorand Integral of time multiplied by absolute value of error and Integral of time multiplied by squared error.

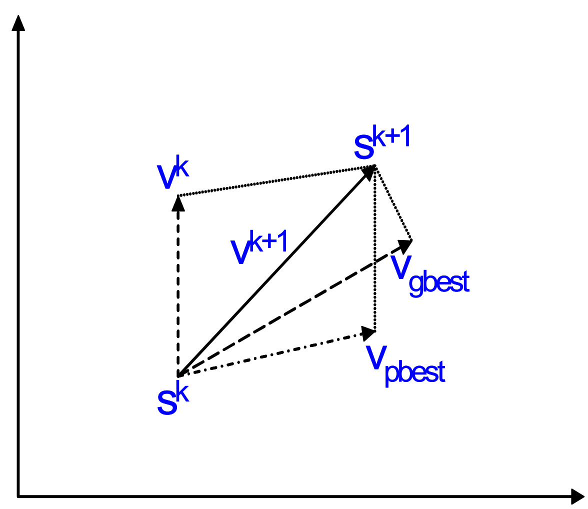

Figure 2: Concept of modification of a searching point by PSO

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

- PSO(Particle Swarm Optimization)is a robust stochastic optimization technique based on the movement and intelligence of swarms.
- PSO applies the concept of social interaction to problem solving.

Section 1 describes the introduction, Section 2 describes the controller tuning techniques, Section 3 explains the simulation results and discussion, Section 4 explains the conclusion, Section 5 inclines the references.

The manipulated input-output process transfer function for the reactor is:

$$G_p(s) = \frac{(-1.1170s \quad .1472)e\hat{}0.5s}{s^2+4.6429s \quad .3821}$$

2. Comparison of tuning techniques

A PID controller has three tuning parameters. If these are adjusted in an ad hoc fashion, it may take a while for satisfactory performance to be obtained. Also, each tuning technician will end up with different set of tuning parameters. Thereis plenty of motivation, then, to develop an algorithmic approach to controller tuning. The controllers used are: Ziegler Nichols, Tyreus-Luyben, ACO and PSO algorithm.

2.1 Ziegler Nichols Method

This closed loop tuning technique was perhaps the first rigorous method to tune the PID controllers. It is widely used method for PID tuning was published by Ziegler-Nichols in 1942. The tuning parameters are tabulated, based on the critical gain and period:

Table 1: Ziegler Nichols Formula

Controller type	k_c	k_i	k_d
PID	$0.6k_{cu}$	$P_{u/2}$	$P_{u/8}$

2.2 Tyreus-Luyben Method

Tyreus and Luyben have suggested tuning parameter rules that result in less oscillatory responses and that are less sensitive to changes in the process condition. Their rules are:

Table 2: Tyreus-Luyben Formula

Controller type	k_c	k_i	k_d
PID	$k_{cu/2.2}$	$2.2p_u$	$P_{u/6.3}$

2.3 Ant Colony Optimization

Ant Colony Optimization (ACO) is a metaheuristic approach for solving hard combinatorial optimization problems. The inspiring source of ACO is the foraging behaviour of real ants. While walking from food sources to the nest and vice versa, ants deposit a substance called pheromone on the ground. Paths marked by strong pheromone concentrations are more probable to be chosen when deciding about a direction to go. This basic behaviour is the basis for a cooperative interaction which leads to the emergence of shortest paths, thus minimizing the length of the path between nest and food source.
ACO algorithms are called autocatalytic positive feedback algorithms. ACO studies artificial systems that take inspiration from the behaviour of real ant colonies and it is used to solve many discrete optimization problems. The foremost features of this algorithm are natural metaphor, stochastic nature, adaptivity, inherent parallelism, and positive feedback. It shows boundless performance with the “ill-structured” problems. ACO local search is a key to obtain good results.

Based on the distribution ranges of ACO the PID parameters obtained are:

K_p=1.2941

K_i=1.3205

K_d=0.3890.

2.4 Particle Swarm Optimization

It was developed in 1995 by James Kennedy (social psychologist) and Russell Eberhart (electrical engineer).

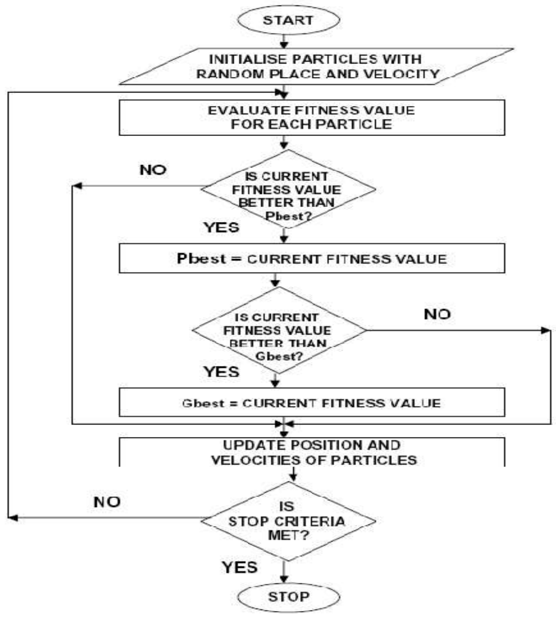

Figure 3: Flowchart of PSO

In PSO algorithm, the system is initialized with a population of random solutions, which are called particles, and each potential solution is also assigned a randomized velocity. PSO relies on the exchange of information between particles of the population called swarm. Each particle adjusts its trajectory towards its best solution (fitness) that is achieved so far. This value is called p_{best}. Each particle also modifies its trajectory towards the best previous position attained by any member of its neighborhood. This value is called *gbest.* Each particle moves in the search space with an adaptive velocity.

The fitness function evaluates the performance of particles to determine whether the best fitting solution is achieved. During the run, the fitness of the best individual improves over time and typically tends to stagnate towards the end of the run. Ideally, the stagnation of the process coincides with the successful discovery of the global optimum.

Let *D* be the dimension of the search space taken into consideration and Xi = [xi1, xi2….x_{iD}]^{T}denote the current position ofi^{th}particle of the swarm, Then: Xi pbest =[x_{i1}^{pbest},x_{i2}^{pbest},….x_{iD}^{pbest}] ^{T} denote the best position ever visited by the particle.Xgbest =[x_{i1}^{gbest},x_{i2}^{gbest},….x_{i2}^{gbest}] ^{T} represents 'gbest',i.e the best position obtained this far by any particle in the population. Vi=[v_{i1},v_{i2},….v_{iD}] ^{T} represents the velocity of i^{th} particle. Vimax = [v_{i1}^{max},v_{i2}^{max} ….v_{iD}^{max}] ^{T} denotes the upper bound on the absolute value of the velocity with which the particle can move at each step.The position and velocity of the particles is adjusted as per the following equation:

$V_{id} = w*v_{id} + c1.*r1 * (x_{id}^{pbest} - x_{id}) + c2 *r2 *(x^{gbest} - x_{id})$ ----- (1)

$V_{id} = \begin{cases} v_d^{max}, & v_{id} > v_d^{max} \\ -v_d^{max}, & v_{id} < -v_d^{max} \end{cases}$ ---- (2)

$x_{id} = x_{id} + v_{id}$ -----(3)

wherec1 and c2 are positive constants, represent the cognitive and social parameter respectively; r1 and r2 are random numbers uniformly distributed in the range [0,1]; w is inertia weight to balance the global and local search ability.

Table 3: PSO Selection Parameters

Population size	100
Number of iterations	100
Velocity constant,c1	2
Velocity constant,c2	2

3. Simulation Results and Discussion

Table 4: Controller Parameters for ZN and TL

Controllers	k_p	k_i	k_d
ZN	1.518	1.460	0.365
TL	0.79062	0.12307	0.3664

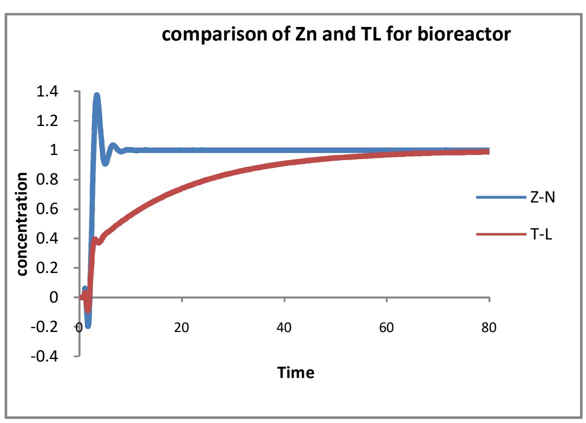

Figure 4:Graph designating ZN nd TL for Bioreactor

Comparing the parameters of the controllers ZN nd TL, ZN is the best method.Overshoot and settling time are small compared to Tl method.Furthermore,ZN is compared with ACO and PSO and it is proved that PSO is the method for optimization.

Table 5: Controller Parameters for ZN,ACO and PSO

Controllers	K_p	K_i	k_d
ZN	1.518	1.460	0.365
ACO	1.2955	1.2957	0.4185
PSO	1.2941	1.3205	0.3890

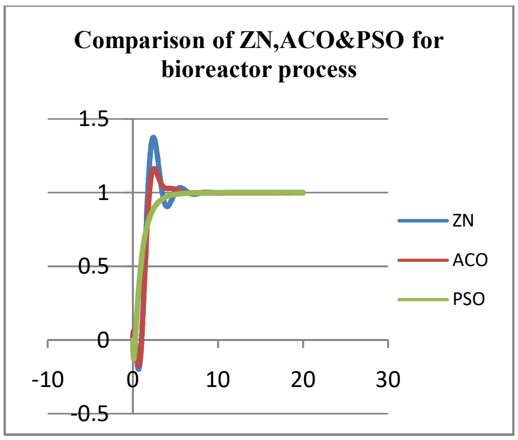

Figure 5:Graph designating ZN,ACO and PSO for Bioreactor process

3.1 Time Domain Specifications

3.1.1 Settling Time: Time required for the response curve to reach and stay with a certain % of the final value.

3.1.2 Rise Time: Time taken by the signal to change from specified low value to specified high value.

3.1.3 Peak Time: Time taken by the system to have maximum value of the curve.

3.1.4 Overshoot: Maximum peak value of the response curve. It occurs when the transitory value exceeds its final value.

Table 6: Time domain specifications

Controllers	Settling Time	Rise Time	Peak Time	Overshoot
ZN	14.72	2.1	3.07	9.35
TL	147	0	0	0
ACO	8.0	0.85	3.36	16
PSO	9.0	0	0	0

3.2 Performance Index

Performance measures which utilize the entire transient response usually assume the form of a time integral of the actuating error function.

3.2.1 ISE ((Integral Square Error):

The ISE is a better criterion for suppressing large errors because a squared error greater than unity contributes more to the integral than does an absolute error.

$$\text{ISE} = \int_0^\infty e^2(t)dt$$

3.2.2 IAE (Integral Absolute Error):

IAE leads to controller which better suppress small errors.

IAE $=\int_0^\infty |e(t)|dt$

3.2.3 ITAE (Integral Time Weighted Absolute Error):

ITAE index is generally preferred because it places greater penalty on small errors occurring at large time. ITAE is the most popular among the four criteria, probably because its use results in the most conservative controller design.

ITAE= $\int_0^\infty t|e(t)|dt$

3.2.4 MSE (Mean Square Error):

This method is best of all since it measures the average of the squares of the error.

Table 7: Performance Index

Controllers	ISE	IAE	ITAE	MSE
ZN	15.88	44.83	46.62	0.0688
TL	54.29	139.2	489.23	0.0362

ACO	13.0	13.98	9.89	0.0649
PSO	13.19	13.91	10.706	0.1306

From the above criteria's (time domain, performance index) it is proved that PSO is the best method comparing to traditional tuning techniques.

3.3 Servo Regulatory

If the process of the control system is to make the process follow changes in set point then it is called servo operation. Reference value changes than disturbance. Regulatory operation serves the purpose of control system to keep the controlled variable constant inspite of changes in load. More disturbance than reference value changes. System that serves good for servo operation will generally not be best for regulation operation.

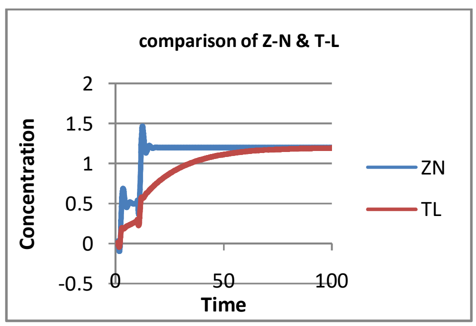

Figure 6: Servo performance of ZN and TL

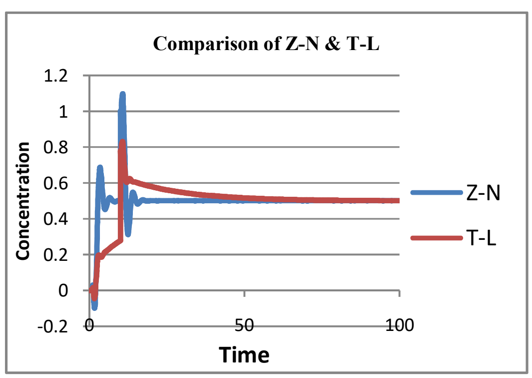

Figure 7: Regulatory performance of ZN and TL

From the above figure ZN and TL controller performs well for both servo and regulatory performance. From this responses it is proves that ZN is functioning well than TL controller.

Furthermore, ZN is compared with ACO and PSO servo regulatory performance and it is proved that PSO works well comparing to other traditional tuning techniques.

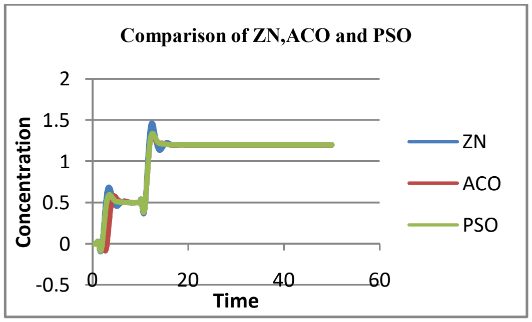

Figure 8: Servo performance of ZN, ACO and PSO

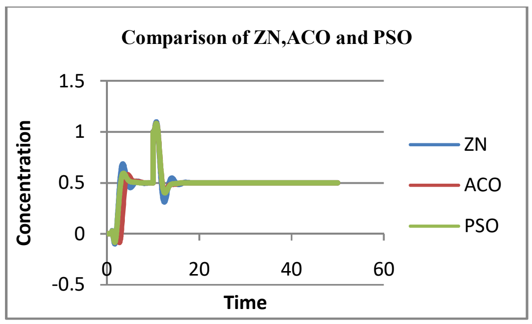

Figure 9: Regulatory performance of ZN,ACO and PSO

3.4 Distribution Ranges of PSO

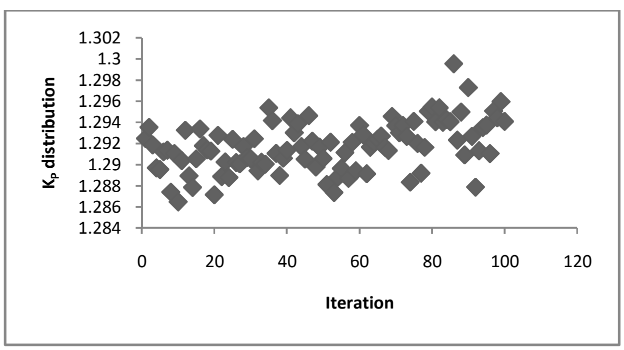

Figure 10: Distribution of K_p for 100th iteration

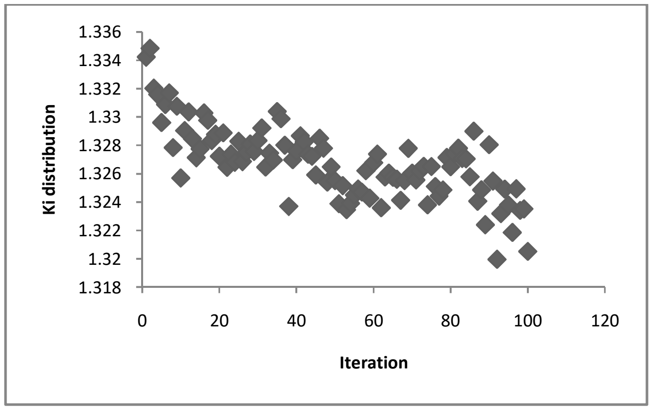

Figure 11: Distribution of K_i for 100th iteration

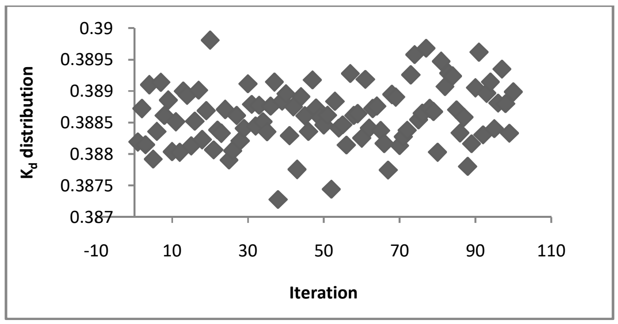

Figure 12: Distribution of K_d for 100th iteration

The PID controller was formed based upon the respective parameters was selected for the 100 iterations and the gbest solution is selected for the set of parameters, which had the minimum error. The PID tuning parameters for this model is

$$K_p=1.2941$$

$$K_i=1.3205$$

$$K_d=0.3890$$

Conclusion

The various results offered above prove the betterness of the PSO tunes PID settings than traditional tuning techniques. Since PSO is based on the intelligence it can be used for both scientific and engineering use. The calculation in PSO is very simple. Compared with the other calculations, it occupies the bigger optimization stability and it can be completed easily. However, the research on the PSO is still at the beginning, a lot of problems are to be resolved. This paper clearly proves that PSO serves well for isothermal chemical reactor process. The same work can be extended for temperature, level, ball and hoop, and interacting system.

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