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Full Length Research Paper

Internal model control - proportional integral derivative controller tuning for first order plus time delayed unstable systems using bacterial foraging algorithm

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This paper proposes a bacterial foraging optimization (BFO) algorithm based approach to tune the parameters of IMC-PID controller for a class of first order plus time delayed (FOPTD) unstable systems with various 'θ/τ' ratios. Initially, the proportional controller based system identification procedure is attempted to convert the higher order unstable process model into an equivalent FOPTD unstable model. Similarly the identification procedure is also carried out for a class of FOPTD unstable models. The converted FOPTD unstable model which shows a nominal model mismatch is then considered for the controller tuning manoeuvre. In this work, BFO algorithm is employed to search the best possible controller parameters such as K_p, K_i, K_d by minimizing the performance index, assigned to supervise the algorithm convergence. The relative efficiency of the BFO based internal model control - proportional integral derivative (IMC - PID) controller tuning has been confirmed through a comparative study with the existing nature inspired algorithms such as particle swarm optimization (PSO) and Ant colony optimization (ACO) algorithms. The robustness of the proposed controller tuning method is validated on an unstable continuous stirred tank reactor (CSTR) model. During this test, the CSTR process model with an introduced model uncertainty in the process gain 'K', process time constant 'τ' 'and the delay time 'θ' are analysed. The result also testifies that the BFO tuned IMC-PID provides a robust performance in reference tracking for the CSTR process model with perturbed model parameters.

Key words: Unstable system, model order reduction, internal model control - proportional integral derivative (IMC - PID) controller, bacterial foraging algorithm, performance index, model uncertainty, robustness.

INTRODUCTION

Although many modern controlling methods have been proposed for industrial process control applications, basic and modified configuration (PID) proportional integral derivative controllers are still widely implemented in the industries to support necessary reference tracking and disturbance rejection operations. The PID controller has a simple structure and provides optimal and robust performance for a wide range of operating conditions for stable, unstable and nonlinear processes.

Various model based studies on fine tuning the PID controllers have provided insight for better understanding of the controller performance for stable and unstable process models. In chemical process industries, important processing units such as polymerization reactor, jacketed continuous stirred tank reactor (CSTR), and continuous stirred tank bioreactor (CSTB) are inherently open-loop unstable by design. To achieve the desired performance, it is essential to operate these process loops in unstable steady state regions (Panda, 2009).

In the control literature, a plethora of PID and modified configuration PID controller tuning methods are

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elaborately examined for time delayed unstable systems by Huang and Chen (1999), Lee et al. (2000), Visioli (2001), Sree et al. (2004), Padhy and Majhi (2006), Chen et al. (2008) and many other researchers. Apart from the above methods, a comprehensive appraisal on the classical controller tuning methods for a class of unstable systems could be found in the book by PadmaSree and Chidambaram (2006).

In recent years, direct synthesis schemes are also widely discussed by the researchers to tune the PID controller with a set-point filter. Jung et al. (1999) have proposed a synthesis method to fine tune the controller parameters for unstable FOPDT systems. Panda (2009) has proposed an internal model control - proportional integral derivative (IMC - PID) controller for stable and unstable systems. Recently, Vijayan and Panda (2011) have discussed the overshoot reduction method for a class of stable and unstable process models using the IMC – PID controller.

Most of the controller tuning methods proposed in the literature requires a reduced order model. But, in real time applications, the process model available may be a second or higher order model. Reduced order modeling has been a universal exercise in control field for an easier explanation of a process model without the loss of its dominant dynamic behaviours (Saptarshi et al., 2012a). In the proposed work, the proportional controller based system identification procedure discussed by Sree and Chidambaram (2006) is attempted to convert the higher order unstable process model into an equivalent FOPTD unstable model considered in this paper. The above system identification procedure is also examined with a class of first order plus time delayed (FOPTD) unstable model with different ‘θ/τ’ ratios.

The reduced FOPTD unstable model is then considered for the controller design procedures. After designing a suitable controller, it is necessary to test its performance/robustness on the process model with assumed model perturbations. The robustness analysis for the PID controller is adequately discussed in the literature by Saptarshi et al. (2011, 2012), Suman et al. (2010, 2012), Shantanu (2011) and many other researchers. In this work the robustness analysis investigated by Bequette (2003) has been chosen to test the IMC-PID controller.

From the recent literature, it is observed that the evolutionary/heuristic algorithm based optimization procedures have emerged as a powerful tool for finding the solutions for a variety of control engineering problems. Soft computing algorithms such as Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Bacterial Foraging Optimization (BFO) and PSO-BFO based hybrid algorithms are extensively addressed by the researchers to tune controllers for a class of process models. Chiha et al. (2012) proposed ACO to tune PID controller for stable systems. Majid et al. (2009), Khalid et al. (2012), Troudi et al. (2012) and Rashag et al. (2012) proposed PSO based controller tuning for a class systems. Korani et al. (2008) and Anguluri et al. (2011) discussed about the hybrid algorithm based controller tuning for stable process model. For stable systems, the overshoot and the error value will be very small and it effectively supports the heuristic algorithm based controller tuning. In case of unstable systems, the controller parameter tuning seems to be difficult task and is limited by ‘θ / τ’ ratio. Therefore heuristic approach requires a modified PID structure such as I-PD or PID controller with a set-point filter (IMC - PID).

Further, in this paper we propose the BFO algorithm based IMC-PID controller tuning for a class of FOPTD unstable process models. BFO algorithm is a nature inspired heuristic algorithm, introduced by Kevin M. Passino in 2002 to design an adaptive controller for a tank liquid level control problem. In this algorithm, a collection of artificial *Escherichia coli* bacteria cooperates to find the best possible solutions in the ‘D’ dimensional search space during the optimization exploration. Many efforts for the enhancement of traditional BFO have been proposed in the literature (Biswas et al., 2007; Chen et al., 2009). Recently, Rajinikanth and Latha (2011) discussed about BFO based PID and I-PD tuning for a class of unstable process models. In this work, error minimization is highly prioritized as a performance measure and it monitors the algorithm, until the controller parameters converge to an optimized value. The work demonstrates that, BFO based PID controller tuning can be performed for unstable systems when the ‘θ /τ’ ratio is below 0.2. PID based tuning results in large overshoot when the ‘θ/τ’ ratio is greater than 0.2, which disrupts the convergence of soft computing based search. Hence, in this work, PID controller with a set-point/prefilter is considered in order to speed up the algorithm search.

In this paper, initially a proportional controller based closed loop system identification is attempted to attain an approximated FOPDT model for a class of first order system with various ‘θ /τ’ ratio, first order system with a zero and higher order systems with time delay. A set-point filter based PID controller parameter tuning is then proposed for the reduced model using Bacterial Foraging Optimization (BFO) algorithm. The effectiveness of the BFO tuned IMC - PID controller is validated with a comparative study with PSO and ACO algorithm. Finally, the robustness of the IMC – PID controller is validated on an unstable CSTR process model with introduced model uncertainty in the process parameters such as ‘K’, ‘τ’ and ‘θ’.

MATERIALS AND METHODS

Model order reduction

Most of the unstable processes are mathematically represented by

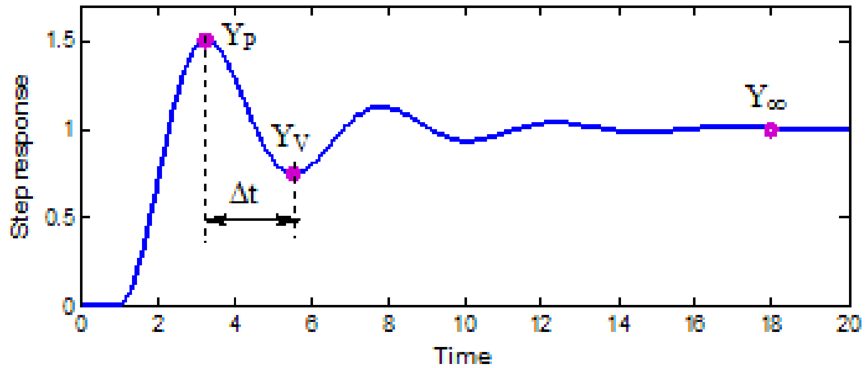

Figure 1. Parameters for proportional controller based system identification / model order reduction. Y_P = First peak value, Y_V = First valley value, Δt = time difference between Y_P and Y_V, Y_∞ = Final steady state value for process output.

the state space models or higher order transfer function models (Bequette, 2003). In order to design a PID controller, it is necessary to have an equivalent reduced order transfer function model. Even though a variety of controlling methods are available for unstable systems, the modified internal model controller (IMC) proposed by Tan et al. (2003) shows a superior performance on a class of unstable process models. The major limitation of the above method is, it requires a FOPDT model to compute the IMC parameters. In this paper, the proportional (P) controller based system identification technique discussed by Sree and Chidambaram (2006) is attempted to convert the HOPTD unstable system into a FOPDT unstable model. This method is very simple since the parameter to be adjusted is only the proportional gain 'K_p'. It is a closed loop test and it can be used for the unstable system having 'θ/τ' ratio ≤ 0.8. Rajinikanth and Latha (2010) reported that, when the identification procedure is performed with a stable underdamped process response, the model mismatch between the original and the identified/reduced system can be significantly minimised.

In the proposed study, we considered three process responses namely; the nearly stable response with approximately null oscillation, response with under damped like oscillation and response with more oscillation.

Steps in 'P' controller based system identification / model reduction procedure for unstable system

Step 1: Consider the closed loop system with 'K_p' only.
Step 2: Excite the system with an unity step signal.
Step 3: Adjust the value of 'K_p' until the closed loop system provides a stable under damped output.
Step 4: Calculate the values of Y_p, Y_v, Δt and Y_∞ (Figure 1).
Step 5: Find the reduced transfer function model of the system using Equations 1 to 8.
Step 6: Validate the model.

The parameters of the process model are identified by considering the following equations discussed by Sree and Chidambaram (2006);

$$P_1 = \sqrt{(1-\xi^2)(K_k - 1)} \tag{1}$$

$$P_2 = \xi\sqrt{(K_k - 1)} + \sqrt{(K_k + 1) + (\xi^2 (K_k - 1)} \tag{2}$$

$$K_k = K \ K_p \tag{3}$$

$$\xi = \frac{-ln(V)}{\sqrt{\pi^2 + \{ln(V)\}^2}} \tag{4}$$

$$V = \frac{Y_\infty - Y_V}{Y_P - Y_\infty} \tag{5}$$

Where: $P1$, P_2, V = variables, ξ = damping ratio, K_k = closed loop gain.

The process parameters can be found by considering the following mathematical relations;

$$\text{Process gain} = K = \frac{Y_\infty}{K_p(Y_\infty - 1)} \tag{6}$$

$$\text{Process time constant} = \tau = \frac{(\Delta t \ P_1 P_2)}{\pi} \tag{7}$$

$$\text{Closed loop delay} = \theta = \frac{(2 \Delta t \ P_1)}{(P_2 \pi)} \tag{8}$$

The identified / reduced FOPTD unstable process model

$$= G_p(s) = \frac{K e^{-\theta s}}{\tau s - 1} \tag{9}$$

Equation 9 provides the reduced FOPTD unstable model of the higher order process. A comparative study is executed between the identified models with the original system in order to find the model with best fit. The FOPDT unstable model which shows smaller contradiction with the original system is adopted to design the controller.

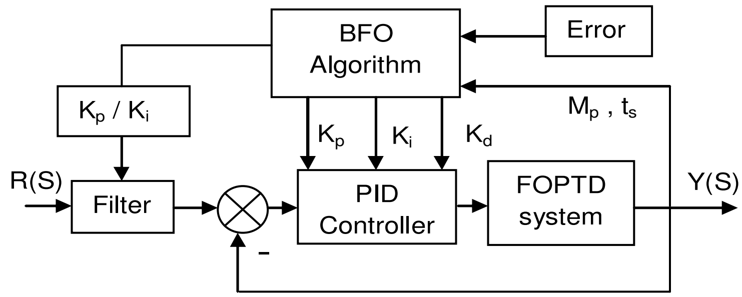

Figure 2. Block diagram for heuristic algorithm based IMC-PID controller tuning.

PID controller structure

In process industries, PID controllers are employed to improve the steady state as well as the transient response of the process plant. In a closed loop control system, the controller continuously adjusts the final control element until the difference between reference input and the process output is zero irrespective of the internal and/or external disturbance signal.

The basic PID controller used in most of the process loop has one of the following structures (Panda, 2009);

Ideal PID structure = $K_p\left(1+\frac{1}{\tau_i s}+\tau_d s\right)$ (10)

Series PID structure = $K_p\left(1+\frac{1}{\tau_i s}\right)\left(\frac{\tau_d s+1}{\alpha\tau_d s+1}\right)$ (11)

Parallel PID structure = $K_p\left(1+\frac{1}{\tau_i s}+\frac{\tau_d s}{\alpha\tau_d s+1}\right)$ (12)

The parallel PID structure presented in Equation 12 is considered in the present study due to its non-interacting configuration. The derivative filter constant is assigned as α= 10.

To reduce the overshoot, a set-point filter is added along with the parallel PID controller (IMC-PID) as shown in Figure 2, and the model of the controller is given in Equation 13.

Controller is = $K_p\left(1+\frac{1}{\tau_i s}+\frac{\tau_d s}{\alpha\tau_d s+1}\right)\left(\frac{1}{T_f s+1}\right)$ (13)

The set-point filter parameter 'T_f' is calculated as $T_f=\tau_i={K_p}/{K_i}$ (Jung et al., 1999).

Bacterial foraging optimization (BFO)

Bacteria Foraging Optimization (BFO) algorithm is a biologically inspired stochastic search technique based on mimicking the foraging (methods for locating, handling and ingesting food) behaviour of *E. coli* bacteria (Passino, 2002; Biswas et al., 2007; Korani et al., 2008). During foraging, a bacterium can exhibit tumbling and/or swimming operation. The tumble action modifies the orientation of the bacterium and during swimming the bacterium will move in its current direction. The basic operations of BFO algorithm is briefly discussed as follows.

Chemo-taxis

This is the initial stage of BFO search. In this process, the bacteria can shift towards the food location with the action of swimming and tumbling via flagella. Through swimming, it can move in a particular way and during tumbling, the bacteria can adjust the direction of exploration. These two operations are continuously executed to move in random paths to find sufficient amount of positive nutrient gradient. These operations are performed by all the bacteria during its entire lifetime.

Swarming

In this process, after the victory towards the best food position, the bacterium which has the knowledge about the best possible path will attempt to communicate to other bacteria by using an attraction signal. The signal communication between cells in *E. coli* bacteria is represented by the following equation;

$$J_{cc}(\theta,P(j,k,l))=\sum_{i=1}^{n}J_{cc}(\theta,\theta^i(j,k,l))=A+B \quad (14)$$

Where

$$A=\sum_{i=1}^{n}[-d_{attract}\ \exp(-W_{attract}\sum_{m=1}^{P}(\theta_m-\theta^i{}_m)^2)] \quad (15)$$

$$B=\sum_{i=1}^{n}[h_{repell}\ \exp(-W_{repell}\sum_{m=1}^{P}(\theta_m-\theta^i{}_m)^2)] \quad (16)$$

Where J_{cc} *(θ, P (j, k, l))* represents objective function value, 'n' is the total number of bacterium, 'P' the total parameters to be optimised. The other parameters such as *'$d_{attract}$'* are the depth of attractant signal released by a bacteria and *'$W_{attract}$'* is the width of attractant signal. The signals 'h_{repell}' and 'W_{repell}' are the height and width of repellent signals between bacterium. (Attractant is the signal for food source and repellent is the signal for noxious reserve).

Reproduction

In swarming process, the bacteria accumulated as groups in the positive nutrient gradient and which may increase the bacterial density. Later, the bacteria are sorted in descending order based on its health values. The bacteria which have the least health will expire and the bacteria with the most health value will split into two and breed to maintain a constant population.

Elimination-dispersal

Based on the environmental conditions such as change in temperature, noxious surroundings, and availability of food, the population of a bacteria may change either gradually or suddenly. During this stage, a group of the bacteria in a restricted region (local optima) will be eliminated or a group may be scattered (dispersed) into a new food location in the search space. The dispersal possibly flattens the chemo-taxis advancement. After dispersal, sometimes the bacteria may be placed near the good nutrient source and it may support the chemo-taxis, to identify the availability of other food sources. The above procedure is repeated until the optimized solutions are achieved.

BFO based IMC-PID tuning procedure

In a closed loop system, the controller has to provide closed loop stability, smooth reference tracking and load disturbance rejection (Johnson and Moradi, 2005). The main objective of the controller is to make the peak overshoot (M_p), settling time (t_s) and final steady state error (E_{ss}), as small as possible. In BFO based approach, the Cost Function (CF) is used to appraise the performance of the closed loop system during the optimization search. The minimization of Integral Square Error (ISE) and Integral of Time weighted Squared Error (ITSE) criterion shown in Equations 17 and 18 are preferred as the 'CF'.

$$ISE = \int_0^T e^2(t)\,dt = \int_0^T [r(t) - y(t)]^2 \; dt \tag{17}$$

$$ITSE = \int_0^T t\; e^2(t)\,dt = \int_0^T t\,[r(t) - y(t)]^2 \; dt \tag{18}$$

Where e(t) = error , r(t) = reference input , and y(t) = process output.

Majid et al. (2009) initially proposed the multiple objective functions for PSO based controller parameter optimization. In this method, along with CF, values like M_p, t_s, E_{ss}, rise time (t_r), Gain Margin (GM) and Phase Margin (PM) are considered. This approach can work good for stable system models. For unstable models, the peak overshoot (M_p) is unavoidable and also the values like GM and PM cannot be obtained during the optimization search. Hence, in this work we propose a simple performance criterion with four functions, such as CF, M_p, t_s, and E_{ss} as presented in Equation 19.

$$J(K_p, K_i, K_d) = (w_1.CF) + (w_1.M_p) + (w_1.t_s) + (w_1.E_{ss}) \tag{19}$$

Where: w_1, w_2, w_3, w_4 are weighting parameters; *CF - ISE; ITSE;* M_p, T_s and E_{ss} are additional performance index obtained from the process output.

Equation 19 shows a multi objective criterion and it has four terms accompanied by a weighting factor 'w'. The above equation can work fine for a class of stable and unstable process models.

PID controller tuning

The PID tuning process is employed to find the best possible values for K_p, K_i and K_d from the three dimensional search space by minimizing the objective function (Equation 19). During this search, the performance criterion '$J(K_p, K_i, K_d)$' guides the algorithm to get appropriate values for the controller parameters. In the literature, there is no clear guideline to assign the algorithm parameters for the evolutionary algorithm. In this study, we propose a simple method to assign the parameters for BFO algorithm in order to reduce the convergence time during the optimization search.

The BFO algorithm search is initiated with the following parameters: dimension of search is three (K_p, K_i, K_d); number of bacteria is chosen as twelve; number of chemo tactic steps is set to six; number of reproduction steps, length of a swim and number of elimination-dispersal events are considered as three; number of bacterial reproduction is assigned as six, probability for bacteria eliminated /dispersed is set as '0.3'. Other parameters are assigned as: $d_{attract} = 0.3$, $W_{attract} = 0.5$, $h_{repell} = 0.6$ and $W_{repell} = 0.6$.

The following values are assigned in the performance index during the optimization search:

i) The three dimensional search space is bounded as:

K_p: -2 to 5; K_i : -1 to 1; and K_d : -1 to 3 .

ii) The steady state error (E_{ss}) in the process output is assigned as zero.
iii) The settling time 't_s' is preferred as <50% of the maximum simulation time.
iv) The overshoot in the process output 'M_p' is chosen as <10% of the reference signal.
v) The reference input signal 'R(s)' is unity.
Vi Five trials are carryout for each algorithm and the best value among them is considered.

Comparative study

The performance of proposed BFO algorithm is compared with the following algorithms:

Particle swarm optimization (PSO)

Dimension of search space is three (K_p, K_i, K_d); number of swarm and bird step is considered as twelve; the cognitive (C_1) and global (C_2) search parameter is assigned the value of 2, the inertia weight discussed by Rashag et al. (2012) is considered in this study.

Ant colony optimization (ACO)

Search dimension is assigned as three (K_p, K_i, K_d); number of ants are set as twelve, the algorithm constants such as α, β and ρ are allotted with a constant value of 0.75 (Chiha et al., 2012).

For these algorithms, the performance index presented in Equation 19 is considered. The maximum iteration for the optimization search is fixed as 250.

Robustness analysis

After finding the best possible PID parameters, it is necessary to test the performance and robustness of the controller. Robustness can be investigated by introducing uncertainty in the process model. Let the unstable FOPDT process be defined by the following transfer function;

$$G_p(s) = \frac{K e^{-\theta s}}{\tau s - 1} \tag{20}$$

The uncertainty in the above process model is introduced in the gain *'K'*, process delay *'θ'* and the process time constant *'τ'*.

Let the uncertainty in *'K'* be *'ΔK'*, 'θ' be *'Δθ' and 'τ'* be *'Δ τ'*. The process transfer function with parameter perturbation can be represented as;

$$\overset{\Delta}{G}_p(s) = \frac{(K \pm \Delta K) e^{-(\theta \pm \Delta\theta)s}}{(\tau \pm \Delta\tau)s - 1} \tag{21}$$

RESULTS

Here, we will discuss the usefulness of the proportional (P) controller based closed loop system identification and model reduction method and the superiority of the BFO tuned IMC-PID controller with the help of some typical unstable process models.

Process 1: Considering an unstable FOPTD process discussed by Sree and Chidambaram (2006):

$$G_p(s) = \frac{1e^{-0.1s}}{s-1} \tag{22}$$

This system has 'θ /τ' ratio of 0.1.

Initially, the 'P' controller based system identification procedure is attempted to identify the approximated unstable process model. During this study, a closed loop identification test with three different 'K_p' value is considered and the identified model parameters and its corresponding values are presented in Table 1. The model identified with K_p = 6.5 (that is K=1.0038, τ =0.9235, and θ_c = 0.1288) shows a best fit with the original model represented in Equation 22, compared to other models identified using K_p = 5.5 and K_p = 7.

The heuristic algorithm based IMC-PID parameter tuning is executed with the above discussed model. Table 2 depicts the controller parameter values and its performance measure (ISE, IAE, ITSE, ITAE) for BFO, PSO and ACO algorithms. The controller tuned with the identified model is then tested on the original model represented in Equation 22. The reference tracking performance and the corresponding controller output is presented in Figure 3. The BFO tuned IMC-PID provides an improved performance compared to PSO and ACO. (The PSO tuned controller results in overshoot, whereas the ACO provides a sluggish response).

Process 2: Considering an unstable FOPTD process given in Vivek and Chidambaram (2005):

$$G_p(s) = \frac{1e^{-0.5s}}{s-1} \tag{23}$$

This system shows 'θ /τ' ratio of 0.5.

The present method with K_p = 2.2 gives the model parameters as K=1.0002, τ = 0.966 and θ_c=0.4746. The symmetrical relay feedback test proposed by Vivek and Chidambaram (2005) gives the FOPTD unstable model parameters as K=1.0638, τ = 1.0832 and θ =0.5127. Table 1 also depicts the other models identified using K_p = 2.0 and K_p = 2.4. It shows the identified model by the proposed method is closer to that of the actual system given in Equation 23. As stated earlier, the IMC-PID controller is tuned using the above mentioned model. The controller parameters and the closed loop performance comparisons are presented in Table 2. The error values by BFO tuned controller is minimal compared to PSO and ACO tuned controllers. The step response and the controller output are as shown in Figure 3. The response by the BFO tuned IMC-PID is superior compared to other soft computing algorithms.

Process 3: The unstable FOPTD system with θ/τ = 0.8, studied by Padhy and Majhi (2006) is presented below:

$$G_p(s) = \frac{1e^{-0.8s}}{s-1} \tag{24}$$

It has been reported in the literature that, the basic relay based system identification technique can be used for the unstable systems only when θ/τ < 0.693 (Padhy and Majhi, 2006).

Primarily, the system identification for the model (Equation 24) is performed with various values of K_p such as K_p=1.188, K_p= 1.155 and K_p = 1.122. The model identified with K_p= 1.155 (that is K=0.9715, τ =1.0037, and θ_c = 0.8616) is considered in the controller tuning procedure. Heuristic algorithm tuned controller values and its performance measure are presented in Table 1.

Figure 3 depicts the reference tracking performance and the controller outputs. The IMC-PID with the proposed tuning method provides a smooth reference tracking performance without any overshoot compared with the PSO and BFO tuned controller.

The attempted work illustrates that the P-controller system identification procedure can be used to identify the approximate model of the real time system with θ/τ = 0.8.

Table 1. Proportional controller based system identification: parameters and identified models.

Process	K_p	Values from process response				Calculated values					Identified model parameter
		Y_p	Y_m	Y_∞	Δ_t	V	ξ	K_1	P_1	P_2	
1	5.5	1.631	1.087	1.222	0.40	0.3301	0.4000	5.5045	1.9452	3.5369	K=1.001; τ =0.879; Θ_c=0.1400
	6.5	1.807	0.8691	1.181	0.40	0.4982	0.2393	6.525	2.2822	3.1781	K=1.0038; τ =0.9235; Θ_c=0.1288
	7.0	1.907	0.7535	1.166	0.40	0.5567	0.1986	7.0241	2.4055	3.3617	K=1.0034; τ =1.0296; Θ_c=0.1822
2	2.0	2.87	1.631	2.0	1.50	0.4241	0.3004	2.0000	0.9538	2.0583	K=1.0000; τ =0.9374; Θ_c=0.4425
	2.2	2.889	1.242	1.833	1.40	0.5596	0.1967	2.2005	1.0742	2.0174	K=1.0002; τ =0.966; Θ_c=0.4746
	2.4	2.939	0.8658	1.72	1.39	0.7007	0.1163	2.389	1.1706	1.9831	K=0.9954; τ =1.0271; Θ_c=0.5223
3	1.188	16.26	8.495	10.98	6.70	0.4706	0.2606	1.1002	0.3056	1.5340	K=0.9261; τ =0.9998; Θ_c=0.8497
	1.155	14.40	6.266	9.194	6.03	0.5624	0.1949	1.1220	0.3426	1.5264	K=0.9715; τ =1.0037; Θ_c=0.8616
	1.122	12.54	3.997	7.447	5.33	0.6774	0.1292	1.1551	0.3905	1.5198	K=1.0295; τ =1.0069; Θ_c=0.8719
4	0.425	3.370	2.071	2.429	7.88	0.3804	0.3431	2.1515	1.0079	2.1812	K=5.0622; τ =5.5143; Θ_c=2.3181
	0.475	3.306	1.452	2.109	6.87	0.5489	0.2037	1.9017	0.9297	1.9078	K=4.0036; τ =3.8787; Θ_c=2.1313
	0.525	3.319	0.8983	1.916	6.31	0.7254	0.1057	2.0917	1.0390	1.8722	K=3.9842; τ =3.9070; Θ_c=2.230
5	1.2	8.859	4.643	5.997	9.29	0.4731	0.2586	1.2000	0.4320	1.6034	K=1.0001; τ =2.0483; Θ_c=1.5934
	1.275	7.562	2.799	4.626	7.85	0.6223	0.1588	1.2758	0.5185	1.5547	K=1.0006; τ =2.0143; Θ_c=1.667
	1.35	6.812	1.607	3.774	7.03	0.7133	0.1114	1.3605	0.5967	1.6047	K=1.008; τ =2.1427; Θ_c=1.664
6	1.75	3.522	1.724	2.333	12.35	0.5122	0.2290	1.7502	0.8431	1.8686	K=1.0001; τ =6.1932; Θ_c=3.5474
	2.0	3.259	1.201	2.002	10.66	0.6372	0.1550	1.9980	0.9869	1.8932	K=0.9990; τ =6.3400; Θ_c=3.5376
	2.25	3.117	0.8264	1.809	9.65	0.7512	0.0941	2.2361	1.1180	1.9064	K=0.9938; τ =6.547; Θ_c=3.6026
7	2	1.611	1.041	1.292	20	0.4214	0.2652	5.7619	2.1040	3.2427	K=2.8810; τ =43.435; Θ_c=8.2615
	2.5	2.014	0.6979	1.225	20	0.6369	0.1421	5.7619	2.1600	2.9289	K=2.3048; τ =40.276; Θ_c=9.3898
	2.75	2.215	0.4359	1.190	20	0.7702	0.0828	5.7619	2.1747	2.7873	K=2.0952; τ =38.589; Θ_c=9.9338

Process 4: We consider an unstable FOPDT process as given below:

$$G_p(s) = \frac{4e^{-2s}}{4s-1} \tag{25}$$

The process has a gain (K) = 4, process time constant (τ) = 4 and time delay (θ) =2. For this process 'θ /τ' is 0.5. Many studies have proposed different PID settings for the above model and the values are clearly presented in the literature (Jung et al., 1999; Huang and Chen, 1999; Visioli, 2001; Sree et al., 2004; Padhy and Majhi, 2006; Chen et al., 2008; Panda, 2009).

Proportional controller based system identification is attempted for the process and the identified models are presented in Table 1. The model identified with K_p= 0.475 gives the model parameter as K=4.0036, τ = 3.8787 and θ_c =2.1313. The evolutionary algorithm tuned controller parameters and its corresponding error values are presented in Table 2. The error values such as IAE, ITSE and ITAE by the BFO algorithm is comparatively higher than PSO and ACO. From Figure 3, the observation is that, the BFO tuned IMC-PID offers an enhanced setpoint tracking response compared to other algorithms. (The PSO and ACO tuned controller results in large overshoot).

Process 5: Let us take an unstable second order process with one unstable pole as stated in Equation 26.

$$G_p(s) = \frac{1e^{-s}}{(2s-1)(0.5s+1)} \tag{26}$$

Various controller settings for the above model could be found in Chen et al. (2008). The evolutionary algorithm based I-PD controller tuning for this process is discussed by Rajinikanth and Latha (2011, 2012).

Different 'K_p' values (that is, 1.2, 1.275, and 1.35) are

Table 2. PID controller parameters and its performance measure values.

Process	Method	Iteration	K_p	K_i	K_d	ISE	IAE	ITSE	ITAE
	BFO	59	3.477	0.5308	0.1051	0.1693	1.934	1.542	22.85
1	PSO	48	1.655	0.6908	0.2699	0.6081	1.982	2.401	9.548
	ACO	97	2.850	0.3082	0.3515	0.3663	3.286	4.453	52.41
	BFO	82	1.7055	0.2744	0.2208	0.9593	3.848	6.023	34.02
2	PSO	74	1.4275	0.3100	0.1177	1.842	3.705	8.415	23.18
	ACO	118	1.5266	0.1022	0.4115	2.636	9.851	37.59	199.5
	BFO	137	1.2553	0.0376	0.4990	9.451	25.02	236.3	854.1
3	PSO	110	1.1885	0.1033	0.2860	6.361	10.12	53.46	136.1
	ACO	185	1.1220	0.0221	0.3114	19.27	38.16	572.3	1494
	BFO	151	0.4223	0.0144	0.2966	4.383	17.03	131.1	632.6
4	PSO	135	0.3788	0.0201	0.3227	4.923	13.26	95.85	331.5
	ACO	167	0.3995	0.0364	0.1933	5.299	12.47	79.51	2779
	BFO	81	1.6096	0.0983	1.0552	2.822	10.50	43.64	231.4
5	PSO	64	1.4733	0.1250	0.9569	3.311	8.515	34.35	129.3
	ACO	94	1.6225	0.1084	1.1054	2.571	9.594	36.90	194.3
	BFO	73	1.7762	0.0527	2.1285	4.601	18.07	156.7	740.9
6	PSO	58	1.5822	0.0712	1.8440	5.923	14.97	135.6	431.4
	ACO	76	1.4391	0.0388	1.4845	9.588	24.26	312.0	975.1
	BFO	81	2.0533	0.0371	0.2015	37.09	50.69	801.7	1774
7	PSO	74	1.7026	0.0519	0.1883	40.23	66.17	1214	4105
	ACO	95	1.9034	0.0394	0.2152	37.58	52.66	812.0	2142
	BFO	63	-1.1633	-0.0515	-0.4775	3.273	4.633	6.244	17.54
8	PSO	57	-1.0566	-0.0384	-0.2720	3.579	5.897	9.009	30.48
	ACO	106	-1.2881	-0.0644	-0.6033	3.376	4.978	7.197	19.99

proposed in the model reduction procedure and the reduced unstable FOPTD models are tabulated in Table 1.

The reduced FOPTD unstable model with K=1.0006, τ = 2.0143, and θ_c =1.667 is considered for the evolutionary algorithm based IMC-PID tuning practice. The controller values and its corresponding error values are given in Table 2. The error value obtained by ACO is lesser, but the number of iteration taken by the ACO is large compared with BFO. Figure 3 shows the closed loop reference tracking and controller output values for BFO, PSO, and ACO tuned controller. The BFO tuned controller offers a very smooth response compared with other methods.

Process 6: Let us consider an unstable third order process with one unstable pole as given in Equation 27.

$$G_p(s)=\frac{1e^{-0.5s}}{(5s-1)(0.5s+1)(2s+1)} \quad (27)$$

For the above process, P-controller based model reduction is proposed with different 'K_p' values (1.75, 2, and 2.25) and the reduced unstable FOPTD models are tabulated in Table 1. The relay feedback test proposed by Liu and Gao (2008) gives the FOPTD unstable model parameters as K=1.0001, τ = 5.7663 and θ =3.2821. The reduced model parameters obtained from the P-controller based identification is very close with the FOPTD model developed by Liu and Gao (2008). In order to tune the IMC-PID controller, the reduced model with K=0.9990, τ = 6.3400, and θ_c =3.5376 is selected from Table 1.

The controller parameters and its corresponding error values are presented in Table 2. The error values such

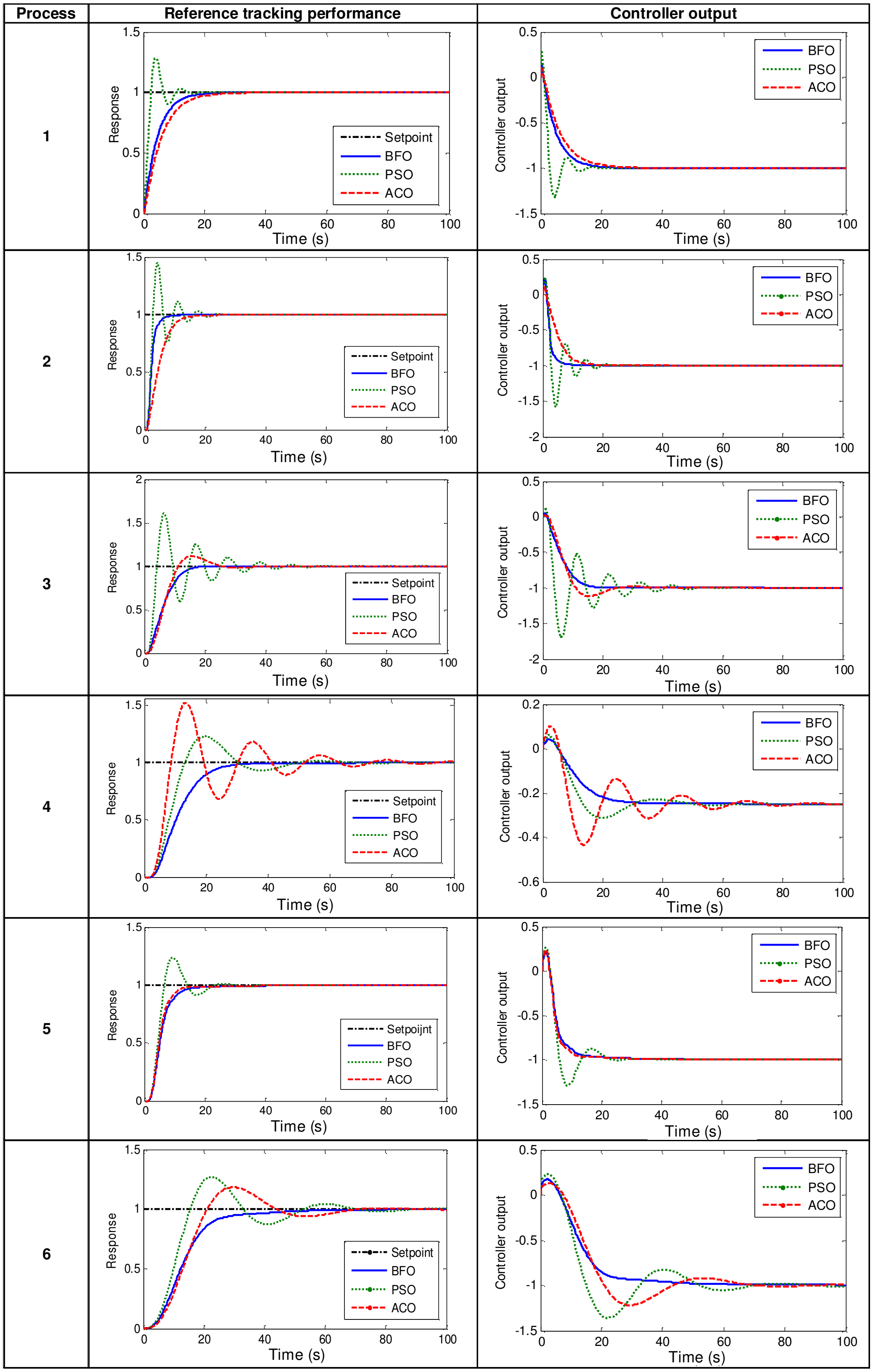

Figure 3. Reference tracking performance and the corresponding controller output for the process models (Process 1 to 6).

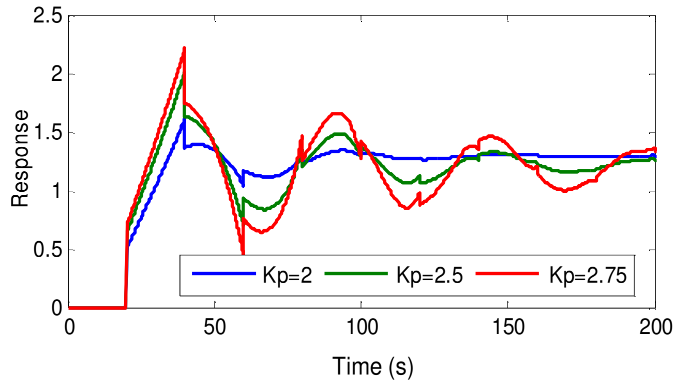

Figure 4. Step response for process 7 with different K_p values.

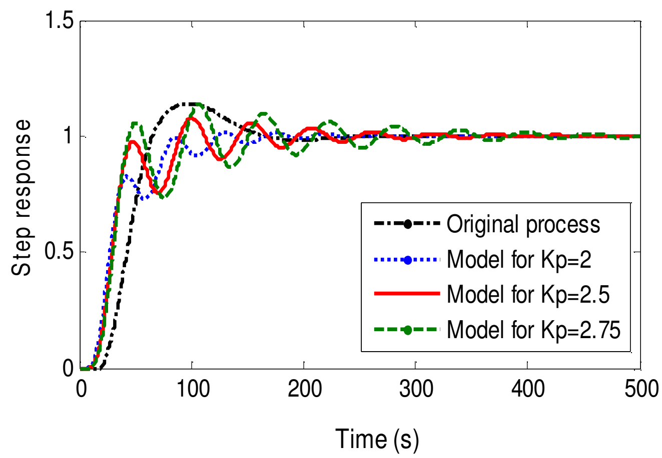

Figure 5. Step response of CSTR model with BFO tuned I-PD controller.

as IAE, ITSE and ITAE are minimal in PSO tuned controller. But the ISE value by the BFO tuned IMC-PID is smaller than PSO and ACO. Figure 3 shows the closed loop reference tracking and controller output values. The PSO and ACO tuned controller provides an oscillatory response with large overshoot, whereas the BFO tuned controller supports a smooth reference tracking with null overshoot.

Process 7: Continuous Stirred Tank Reactor (CSTR) with nonideal mixing considered by Liou and Chien (1991) has the following transfer function model:

$$G_p(s) = \frac{2.22(1+11.133s)}{(98.3s-1)} e^{-20s} \tag{28}$$

This system has one stable zero and an unstable pole.

As stated earlier, model reduction practice is attempted with K_p =2, K_p =2.5, and K_p =2.75. From Figure 4, the observation is that, the first peak value (Y_P), first valley value (Y_V) and time difference between Y_P and Y_V (Δt) are similar for all the cases. Closed loop step test values and the reduced FOPTD unstable models are given in Table 1.

The BFO based I-PD controller setting by Rajinikanth and Latha (2012) provides the following controller parameters: K_p= 1.9130, K_i = 0.0412, and K_d = 0.1094.

By using the I-PD controller, the reference tracking performance between the original (Equation 28) and the reduced models are studied and the corresponding results are presented in Figure 5.

Figure 5 shows that, the identified model with K_p =2.5 gives best fit with the original model compared to other models. This model (K=2.3048, τ=3.8787, θ_c=9.3898) is considered in evolutionary algorithm based IMC-PID tuning.

Figure 6 shows the relationship between the CF and the iteration number for BFO based controller parameter

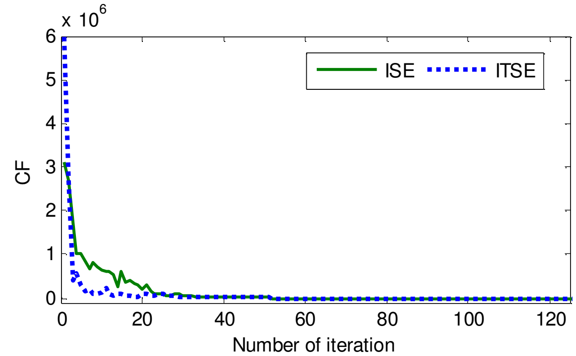

Figure 6. Convergence of cost function for process 7.

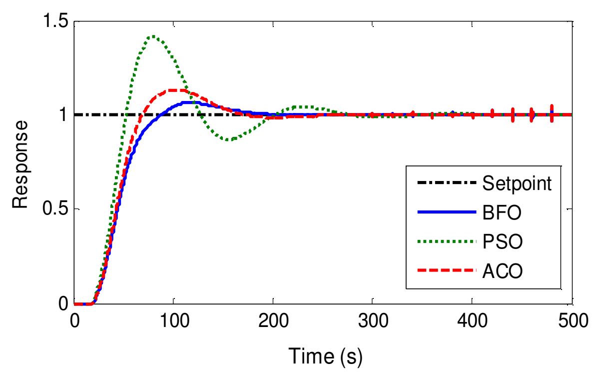

Figure 7. Reference tracking for process 7.

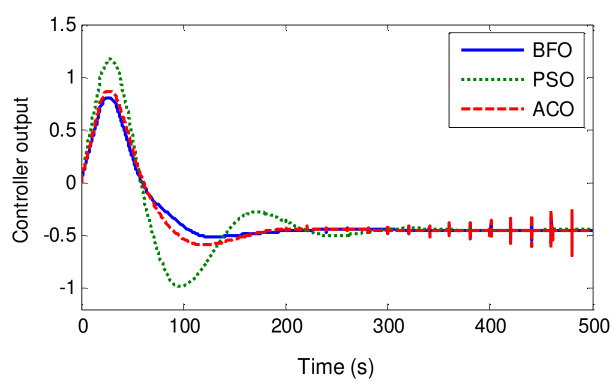

Figure 8. Controller output for process 7.

search. Table 2 presents the controller parameter values and its corresponding error values.

Figures 7 and 8 depicts the reference tracking performance and the corresponding controller output for nonideal mixing CSTR model with the IMC-PID controller. The BFO algorithm tuned controller offers a better setpoint tracking response with minimised error values.

Process 8: Let us take the jacketed CSTR model discussed by Bequette (2003). The process transfer function relating the jacket flow rate to the reactor temperature is;

$$G_p(s) = \frac{-4.4747s - 37.94}{s^3 + 9.332s^2 + 16.89s - 34.45} x\, e^{-\theta s} \qquad (29)$$

Let the value of θ = 0.5 s.

As discussed above, the model reduction is attempted with three different 'K_p' values. The closed loop step test data, supporting values and the identified FOPTD models are presented in Table 3. The highlighted model is considered to tune controller.

In BFO based search, the performance index guides the algorithm in order to achieve the best possible controller parameters. When number of iteration increases, the algorithm converges in the direction of minimal CF as illustrated in Figure 9.

Table 2 shows the optimised controller parameter values obtained using BFO, PSO, and ACO algorithms. The calculated controller parameters are then tested with the original process model represented in Equation 29. Figures 10 and 11 illustrates the reference tracking performance and the corresponding controller output for jacketed CSTR model with the heuristic algorithm tuned IMC-PID controller. The corresponding error values (ISE, IAE, ITSE, and ITAE) are presented in Table 2. The BFO algorithm tuned IMC-PID controller offers a smooth reference tracking with moderately reduced error than the PSO and BFO tuned controllers.

Robustness of the BFO tuned IMC-PID controller is then tested by assuming perturbation in the identified FOPTD unstable process model.

Let the reduced FOPTD unstable model of the jacketed CSTR is:

$$G_p(s) = \frac{-1.1012}{1.076s - 1} x\, e^{-0.9266s} \qquad (30)$$

Let the uncertainty in K, τ and θ is initially taken as ±5% of its original value. A closed loop step test with BFO tuned IMC-PID is conducted and the results are given in Figure 12a. When the uncertainty is upto ±5% of the actual process parameter, the proposed controller offers nearly a stable response for setpoint tracking.

Figure 12b shows the closed loop step response for ±10% of model uncertainty. The uncertainty in 'K' in the given range does not affect the system performance, whereas the change in θ >+5% or τ < -5% results in oscillatory response as shown in Figure 12b.

Setpoint tracking response for ±15% of model uncertainty is shown in Figure 12 (c). When the parameter change in the model is below ±7%, the IMC-PID can track the reference signal effectively. When the

Table 3. Step test data and identified models for CSTR process.

Process	K_p	Values from process response				Calculated values (using Equations 1 to 6)					Identified model parameter
		Y_p	Y_m	Y_∞	Δ_t	V	ξ	K_1	P_1	P_2	
	-0.95	35.86	14.89	22.64	8.9	0.5862	0.1676	1.0462	0.2119	1.4669	$K = -1.1013$; $\tau = 1.0803$; $\theta_c = 0.8185$
8	-0.97	26.91	7.557	15.66	7.2	0.7203	0.1039	1.0682	0.2598	1.4655	$K = -1.1012$; $\tau = 1.076$; $\theta_c = 0.9266$
	-0.99	22.04	3.867	12.21	6.3	0.8487	0.0521	1.0892	0.2983	1.4611	$K = -1.1002$; $\tau = 1.009$; $\theta_c = 0.8769$

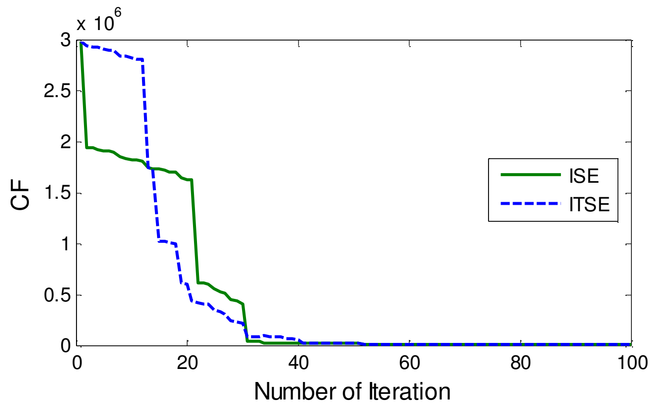

Figure 9. Convergence of cost function with respect to iteration for the CSTR model.

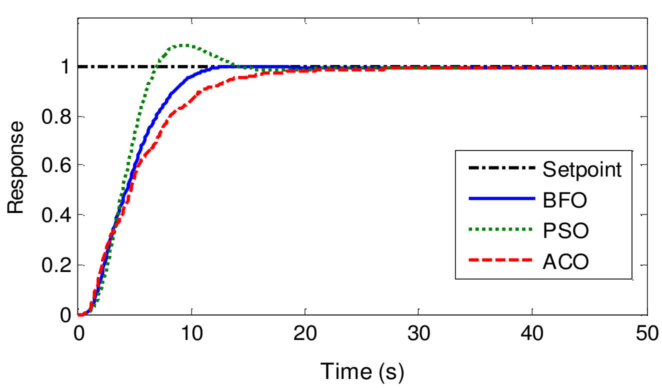

Figure 10. Setpoint tracking performance of jacketed CSTR model with IMC-PID controller.

uncertainty > ±7% the overall response of the closed loop system with proposed controller is oscillatory. From the results, the observation is that, the BFO tuned IMC-PID offers a robust response when the model parameter perturbation is within a limit (that is, < ±7%). Otherwise the jacketed CSTR model will exhibit an oscillatory output.

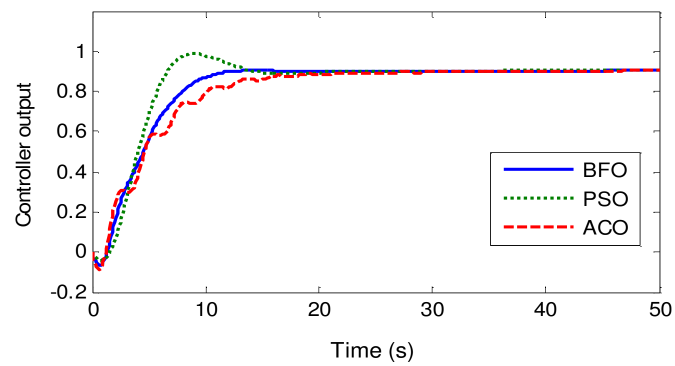

Figure 11. Controller output for jacketed CSTR model.

DISCUSSION

This paper proposed a method for identification/ reduction of unstable process models using closed loop step test. Further, it proposed a BFO based IMC-PID controller for the FOPTD unstable systems.

The relay feedback test and the closed loop step test are the generally accepted identification methods in the field of process control. For unstable systems, the relay feedback test is limited by 'θ/τ' ratio (that is $\theta/\tau < 0.693$). The closed loop step test can be performed with P, PI, or PID controller. The PI or PID based closed loop test is difficult than the P- controller test, due to the number of parameters (For PI test the parameters to be adjusted is two that is K_p, K_i and in PID, the parameters are three, that is K_p, K_i, K_d). Since, a P-controller is widely preferred than the PI and PID. The proposed method is evident that, by carefully selecting the 'K_p', it is possible to achieve a best fit in the identified/reduced model. To validate the accuracy of proposed method, a simulation study is conducted for first order system with various 'θ/τ' ratio, first order system with a zero and higher order systems with time delay.

The accuracy of the BFO tuned IMC-PID has been confirmed through a comparative study with PSO and ACO. From the reference tracking response (Process 1, 2, 3, and 7), it is observed that the response of the PSO

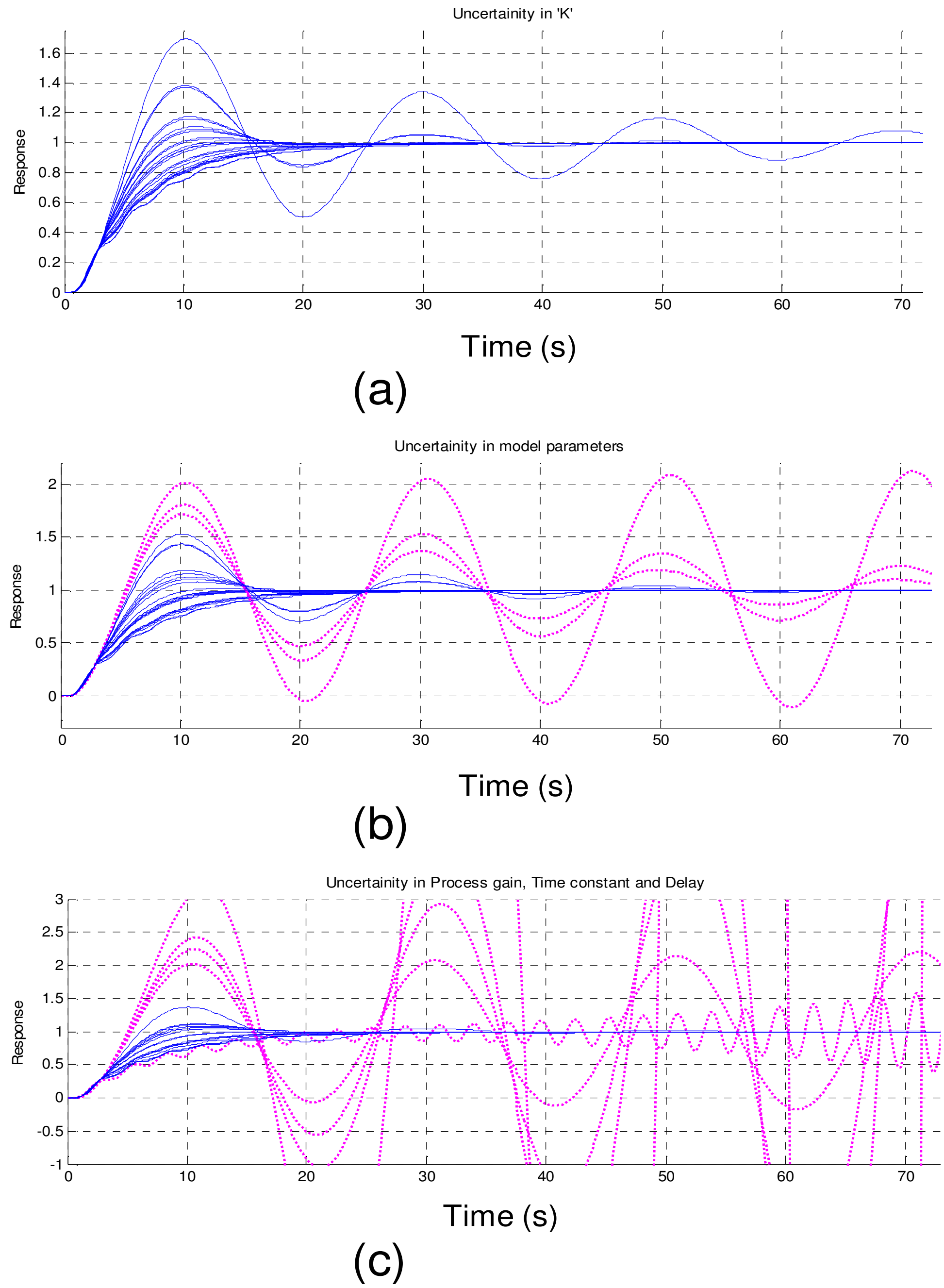

Figure 12. Closed loop step response of jacketed CSTR with perturbed model parameters. (a) Uncertainty of ±5%; (b) Uncertainty of ±10%; (c) Uncertainty of ±15%.

tuned controller is oscillatory, and the ACO tuned controller is sluggish than the BFO tuned IMC-PID. In process 4, the BFO tuned controller provides a smooth response than PSO and ACO. In process 5, 6 – the proposed method provides a better control with significantly reduced error values.

In process 8, a jacketed CSTR model is considered and tested with the proposed method. The robustness of the BFO tuned IMC-PID is tested with parameter uncertainty in K, τ and θ. The simulated result for the uncertainty of ±5% (Figure 12a) shows that the proposed controller is robust. When the uncertainty is ±10%, the increase in ‘θ’ or decrease in ‘τ’ provides oscillatory response, whereas the change in ‘K’ shows a stable steady state reference tracking performance. When the uncertainty is increased to ±15%, the controller provides an oscillatory response. From the result, it is observed that, the BFO tuned IMC-PID provides a robust response up to '±7%' of parameter uncertainty.

Conclusion

A simple proportional controller based system identification/model reduction procedure is attempted to convert the higher order unstable system into a reduced first order unstable system. The identification analysis is tested on a class of first order system with various 'θ/τ' ratio, first order system with a zero and higher order systems with time delay. The attempted method is capable of providing the satisfactory model for the system with $\theta/\tau = 0.8$. By carefully selecting the proportional gain 'K_p' during the identification test, the model mismatch between the original system and the identified system can be significantly minimised. The model with the best fit is then used to tune the IMC-PID controller using the heuristic algorithms like BFO, PSO and ACO. The BFO tuned controller provides smooth reference tracking with reduced peak overshoot, and better closed loop performances such as ISE, IAE, ITSE, and ITAE. The robustness of the BFO tuned IMC-PID controller has been validated on a jacketed CSTR model with perturbed model parameters. The reference tracking performance by the present controller with perturbed model parameter (<±7%) has been found satisfactory [Appendix (Figure a)].

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Appendix

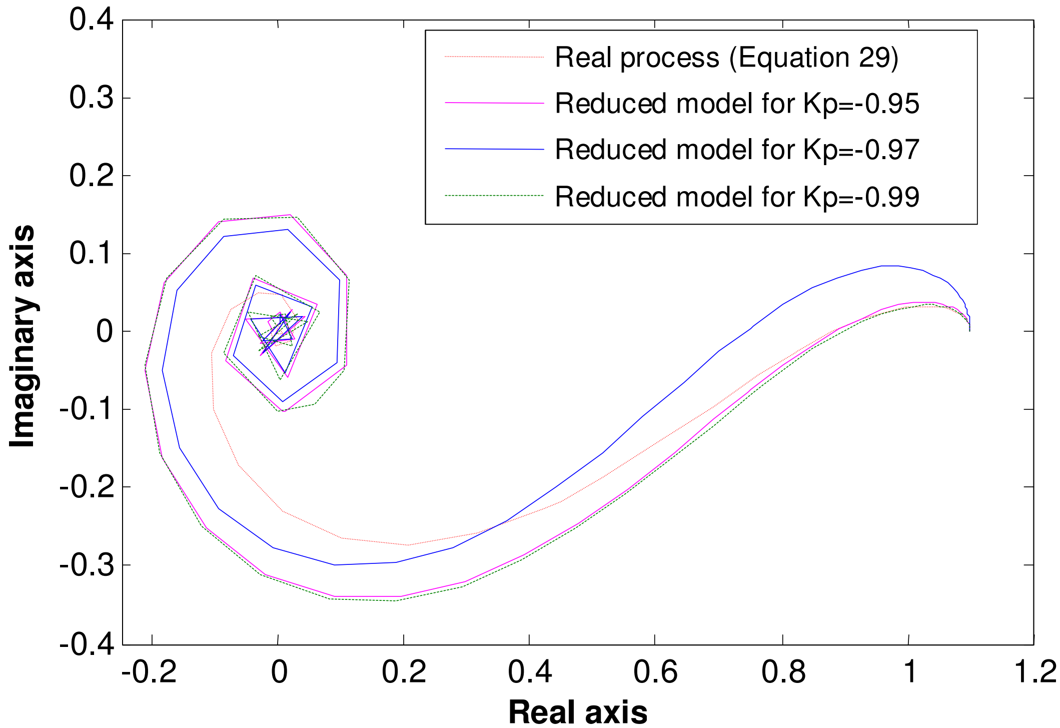

Figure a. Nyquist plots of original and reduced models for Process 8.