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Performance of Gain Scheduled Generic Model Controller Based on BF-PSO for a Batch Reactor

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ABSTRACT
Performance of the gain scheduled Generic Model Controller (GMC) in tracking the batch reactor's optimal temperature profile is considered here. The chosen optimal reactor temperature profile has three switching time interval is obtained by solving optimal control problem off-line by using genetic algorithm. The temperature profile or variation in set point in each time interval is maintained by the proposed controller. The GMC controller parameters are tuned based on the Swarm Intelligence Optimization techniques as Particle Swarm Optimization (PSO) and Bacterial Foraging PSO (BF-PSO) for three switching intervals separately and the integrated performance of gain scheduled GMC has been tested with the batch reactor. The performance of the gain scheduled GMC controller is compared with the single tuned GMC and it provided minimum performance index Integral Square Error (ISE) and Integral Absolute Error (IAE) with improved response for multiple set point tracking.

Key words: GMC, batch reactor, PSO, BF-PSO, optimization, temperature profile

INTRODUCTION
Batch reactors are frequently used in chemical, petro-chemical and bio-chemical industry for the production of various quality products. Processes used are discontinuous and varied. Indeed they are characterized by non-stationary and non-linear system (Baghli and Benyeltou, 2006). The control of a batch reactor consists of the process like filling the reactor with the raw materials; allow it to react by controlling the reactor temperature to meet the required processing condition and shutting down the batch reactor and emptying the reactor. The next batch is started with new filling materials. The heat will be supplied at the starting of the reaction to obtain the desired reaction temperature and then it will be cooled to maintain the proper reaction temperature to get the highest product yield. Production of value added goods in small quantities like medicine in pharmaceutical industries while controlling the polluting waste resources and losses of raw material remains a significant aim of the fine chemical industries. As a result, functioning of the batch reactors at its optimum situation is critical (Aziz *et al*., 2000).

The best possible control of batch reactors has been recognized as main concentration in the precedent. The primary aim is to find out the optimum reactor temperature profile which yield the utmost desired product and decrease the bi-product as the multi-objective optimization problem. Designing a controller to implement the optimal control profiles or tracking the dynamic set point becomes an important area of research for intrinsically dynamic batch processes in recent years. In an exothermic batch reactor, temperature overshoot is usually avoided because it can cause runaway due to the large amount of heat released at the elevated reactor temperatures. Several authors (Aziz *et al.*, 2000; Mujtaba *et al.*, 2006) have proposed the control system that estimates the amount of heat is being released in the reactor and use it in a feed forward control to compensate the consequence of the heat released.

For solving complex engineering problems, many optimization techniques are emerged by inspiring the social behaviour of swarm of fish, bees and other animals. PSO is a robust stochastic evolutionary computation method developed based on the movement of swarms looking for most fertile feeding location (Hassanzadeh and Mobayen, 2008). Comparatively a new evolutionary computation algorithm named as Bacterial Foraging scheme has also been introduced and received more attraction by the researchers Passino (2002). These optimization algorithms have been applied in various fields like Ad-hoc networking (Sabari and Duraiswamy, 2010), Image processing (Saadi *et al.*, 2010; Ouadfel and Batouche, 2007), Artificial intelligence (Qasem and Shamsuddin, 2010), constrained optimization problem solution (Lu and Chen, 2011) etc.

In the design of optimal control field, to obtain optimal controller parameters, many researchers introduced advanced controllers such as PID auto tuning or self tuning (Ustun, 2007), model based adaptive control, model predictive control (Ansarpanahi *et al.*, 2008), fuzzy control (Ali, 2011), artificial neural network, GA based control (Hassanzadeh *et al.*, 2008; Mosavi, 2011), optimal control, expert control and robust control (Ajlouni and Al-Hamouz, 2004). However, all these controllers required some kind of process model and high-level expertise. It is difficult to develop a general-purpose, user-friendly and smart control system based on these control methods. To keep away from these constraints, the computational intelligence has proposed Particle Swarm Optimization (PSO) and Bacterial Foraging that has opened paths to a new generation of an advanced process control. In recent times, these techniques are mostly preferred for tuning of the PID controller (GirirajKumar *et al.*, 2010; Hassanzadeh and Mobayen, 2008; Korani *et al.*, 2009; Pillay and Govender, 2007; Hooshmand, 2008).

In advanced process control, recently many model based control schemes have been developed. Generic Model Control (GMC) approach has been introduced to design the control action for the non linear process which include the process model itself in the control algorithm structure (Lee and Sullivan, 1988). In this paper, the gain scheduling of GMC controller parameters K_1 and K_2 for each switching time interval has been implemented by using these Particle Swarm Optimization and Bacterial Foraging techniques.

BATCH REACTOR MODEL

A complex reaction scheme is a representative of many industrial reactions (Baghli and Benyeltou, 2006). The batch reactor used by Cott and Macchietto (1989), Aziz *et al.* (2000) and Sujatha and Pappa (2011) is shown in Fig. 1. Reactions I and II are given by Eq. 1:

$$\begin{aligned} A + B &\rightarrow C \\ A + C &\rightarrow D \end{aligned} \qquad \text{Reactions I and II (1)}$$

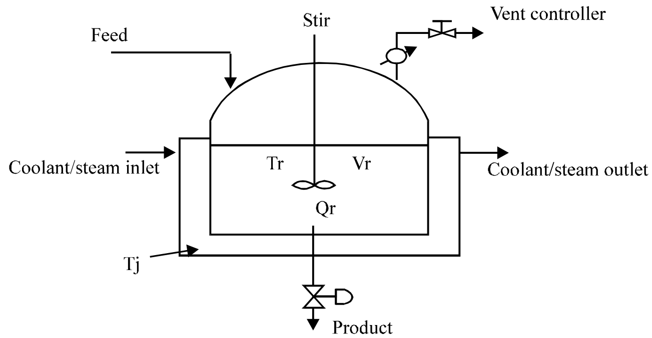

Fig. 1: Schematic diagram of a jacketed batch reactor

where, A, B are the raw materials, C is the desired product and D is the waste product. A batch reactor is inherently dynamic process. Therefore, its model results in a system of differential and algebraic equations. The model equations for the batch reactor can be written as:

$$\frac{dM_A}{dt} = -R_1 - R_2 \tag{2}$$

$$\frac{dM_B}{dt} = -R_1 \tag{3}$$

$$\frac{dM_C}{dt} = R_1 - R_2 \tag{4}$$

$$\frac{dM_D}{dt} = R_2 \tag{5}$$

$$\begin{aligned} R_1 &= k_1 M_A M_B \\ R_2 &= k_2 M_A M_C \end{aligned} \tag{6}$$

$$k_1 = \exp\left(\frac{k_1^1 - k_1^2}{(Tr + 273.15)}\right) \tag{7}$$

$$k_2 = \exp\left(\frac{k_2^1 - k_2^2}{(Tr + 273.15)}\right) \tag{8}$$

$$\frac{dTr}{dt} = \frac{(Q_r + Q_j)}{M_r C_{pr}} \tag{9}$$

$$\frac{dTj}{dt} = \frac{(T_j^{sp} - T_j)}{\tau_j} - \frac{Q_j}{V_j \rho_j C_{pj}} \tag{10}$$

$$Q_r = -\Delta H_1 R_1 - \Delta H_2 R_2 \tag{11}$$

Table 1: Nominal values of the parameters

Constant	Parameters	Values
C_{pA}	Specific heat capacity of component A	18.0 kcal $kmol^{-1}$°C
C_{pB}	Specific heat capacity of component B	40.0 kcal $kmol^{-1}$°C
C_{pC}	Specific heat capacity of component C	52.0 kcal $kmol^{-1}$°C
C_{pD}	Specific heat capacity of component D	80.0 kcal $kmol^{-1}$°C
ΔH_1	Heat of reaction of reaction 1	-10000.0 kcal $kmol^{-1}$
ΔH_2	Heat of reaction of reaction 2	-6000.0 kcal $kmol^{-1}$
C_p	Mass heat capacity of reactant	0.45 kcal kg^{-1}°C
C_{pj}	Molar heat capacity of component j	0.45 kcal g^{-1}°C
U	Heat transfer coefficient	9.76 kcal min^{-1} m^{2}°C
ρ_j	Density	1000.0 kg^{-1} m^3
k_1^1	Pre-exponential rate constant for reaction 1	20.9057
k_1^2	Pre-exponential rate constant for reaction 1	10000
k_2^1	Pre-exponential rate constant for reaction 2	38.9057
k_2^2	Pre-exponential rate constant for reaction 2	17000
V_j	Jacket volume	0.6921 m^3
A	Heat transfer area	6.24 m^2
Mr	Number of moles of component	1560 kg
τ_j	Jacket time constant	3.0 min

$$M_r = M_A + M_B + M_c + M_D \tag{12}$$

$$C_{pr} = \frac{C_{pA}M_A + C_{pB}M_B + C_{pC}M_C + C_{pD}M_D}{M_r} \tag{13}$$

$$Q_j = UA(T_j - T_r) \tag{14}$$

where, in the initial values of the above mentioned process parameters are [M_A, M_B, M_C, M_D, T_j, T_r] = [12.0, 12.0, 0.0, 0.0, 20.0, 20.0] at t = 0, respectively. The reactor temperature is used as the control variable and is bounded between 20 and 100°C and the jacket temperature is the manipulated variable and it is bounded between 20 to 120°C. The batch time is fixed to 120 min. All the nominal parameters and constant values used in the model equations (Sujatha and Pappa, 2010; Sujatha and Pappa 2011) are given in Table 1.

OPTIMAL TEMPERATURE PROFILE GENERATION

Genetic Algorithm (GA) is one of the modern optimization methods and the principle is based on the Darwinian Theory of evolutionary process (Mosavi, 2011; Asfaw and Saiedi, 2011). Here, GA is used to obtain the optimal temperature profile in offline. The fitness function for GA is expressed as given the initial charge per unit volume of the reactor, for the fixed batch time optimize the reactor temperature profile so as to maximize the conversion of the desired product and to minimize the waste product is subject to the constraints on the reactor temperature and constraints on the waste product (Sujatha and Pappa, 2011). The obtained optimized temperature profile is [93→92.34→93.57] that yields the maximum product and is shown in Fig. 2.

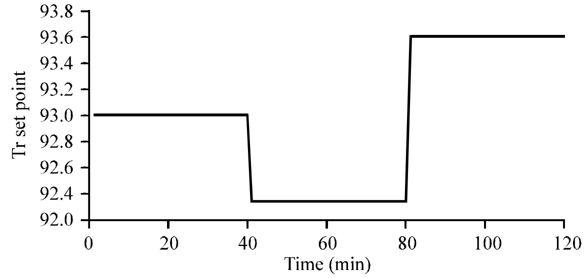

Fig. 2: Optimum temperature profile obtained from GA

PSO AND BF-PSO TUNED GENERIC MODEL CONTROL (GMC)

In this study, PSO and BF-PSO techniques are used to optimize the GMC controller parameters. The GMC algorithm can be written as:

$$\frac{dx}{dt} = k_1(x_{sp} - x) + k_2\int(x_{sp} - x)dt \tag{15}$$

where, x is the current value and x_{sp} is the desired value of the control variable. The first expression in the algorithm is to bring back the process to steady state due to change in dx/dt. The second expression is introduced to make the zero offset.

For temperature control of the batch reactor, a process model relating the reactor temperature (T_r) to the manipulated variable, the jacket temperature (T_j) is required. Assuming that, the amount of heat retained in the walls of the reactor is small in comparison to the heat transferred in the rest of the system, the following model is given based on the energy balance around the reactor contents:

$$\frac{dT_r}{dt} = \frac{Q_r + UA(T_j - T_r)}{W_r C_{pr}} \tag{16}$$

Replacing x with T_r in the general algorithm the control formulation of GMC is given by the Eq. 17:

$$T_j = T_r + \frac{W_r C_{pr}}{UA}\left[k_1(T_{rsp} - T_r) + k_2\int(T_{rsp} - T_r)dt\right] - \frac{Q_r}{UA} \tag{17}$$

where, T_j gives the required jacket temperature trajectory so that the reactor temperature T_r, follows the desired trajectory incorporating the values of GMC tuning parameters k_1 and k_2. These parameters are tuned by using standard PSO and BF-PSO techniques for these three switching interval [93→92.34→93.57] as shown in Fig. 3.

Particle swarm optimization (PSO): PSO is a computation intelligent technique, which was motivated by the organisms' behaviour such as schooling of fish and flocking of birds. The major advantage of PSO is that it employs the physical movements of the individuals in the swarm and has a flexible and well-balanced mechanism to enhance and to adapt the global and local exploration abilities (Hassanzadeh and Mobayen, 2008). The global optimizing model is described as follows:

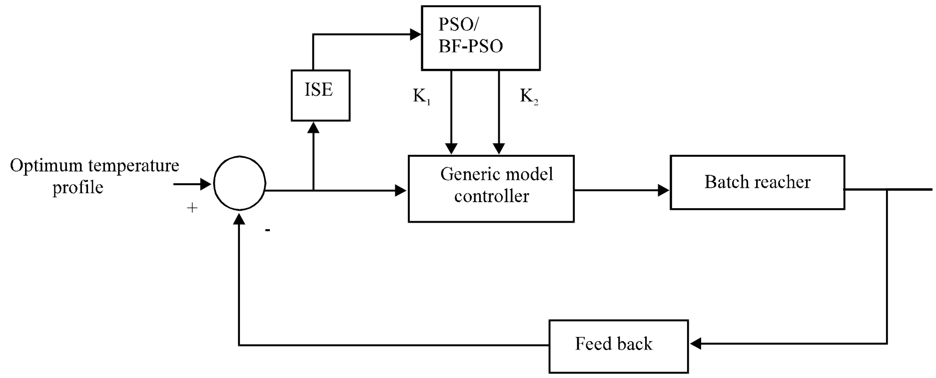

Fig. 3: Proposed controller scheme

$$\begin{aligned} V_{id}^{t+1} &= \omega V_{id}^{t} + C_1 r_1 (P_{best}^{t} - x_{id}^{t}) + C_2 r_2 (g_{best}^{t} - x_{id}^{t}) \\ x_{id}^{t+1} &= x_{id}^{t} + V_{id}^{t} \end{aligned} \tag{18}$$

where, V_{id} is the velocity of particle I, representing the distance to be travelled by this particle from its current position, t is the number of iterations, x_{id} represents the particle position, C_1 and C_2 are the positive constant parameters, r_1 and r_2 are the random functions in the range [0 , 1], P_{best} (local best solution) is the best position of the i^{th} particle, g_{best} (global best solution) is the best position among all particles in the swarm, and ù is the inertia weight which is very important for the convergence behaviour of PSO. A suitable value usually provides a balance between global and local exploration abilities and consequently results in a better optimum solution. Then the following equation is used to adjust to enable quick convergence:

$$\omega = \omega_{max} - (\omega_{max} - \omega_{min})k / k_{max} \tag{19}$$

where, ω_{max} is the initial weight, ω_{min} is the final weight, k is the current generation and k_{max} is the maximum number of generation. Particles' velocities on each dimension are limited to a maximum velocity V_{max}.

Bacterial foraging-PSO algorithm (BF-PSO): It is the combination of bacterial foraging and particle swarm optimization algorithm proposed by Korani *et al.* (2009). In this algorithm, PSO ability is used to exchange social information and BF used in finding a new solution by elimination and dispersal. BF algorithm is based upon search and optimal foraging decision making capabilities of the *E. coli* bacteria. Each bacterium tries to maximize its obtained energy per each unit of time expended on the foraging process and avoiding noxious substances. It undergoes four stages namely chemo-taxis, swarming, reproduction, elimination and dispersal. Chemo-tactic movement is continued until a bacterium goes in the direction of positive nutrient gradient (Shen *et al.*, 2009) (i.e., increasing fitness). The flow chart of BF-PSO has been given in Fig. 4.

RESULTS AND DISCUSSION

The number of swarms in the PSO algorithms and number of bacteria in BF-PSO algorithms are varied and the control parameters obtained from these techniques are presented in the

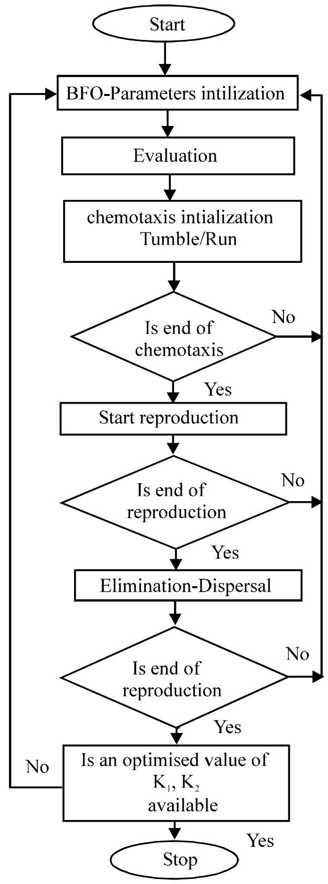

Fig. 4: Flow chart for BF-PSO

Table 2: PSO tuned GMC Parameters

	Time interval (0-40) min		Time interval (40-80) min		Time interval (80-120) min	
Number of iterations (Swarms)	K_1	K_2	K_1	K_2	K_1	K_2
10	5.0133	0.3515	4.2243	1.836	6.6776	0.8332
20	5.0605	-0.0505	5.5780	-0.9292	5.9540	2.6751
30	4.7613	1.7015	4.0652	1.3595	5.3578	2.2008
40	4.3062	0.386	5.0528	2.1784	4.689	2.2711
50	4.3062	0.386	5.0661	2.2534	5.1112	2.1578
60	4.1692	0.4156	4.7885	1.8736	4.8489	2.2918
70	4.3696	0.4151	5.0983	2.0976	4.8751	1.8903
80	4.2984	0.3664	4.9563	1.9615	4.9623	2.1338
90	4.3442	0.4397	4.9568	2.0655	4.9244	1.9998
100	4.3151	0.3781	5.0009	2.2092	4.9306	2.0593
120	4.2979	0.3905	5.0074	2.0576	4.9335	2.0379
150	4.3117	0.3993	5.0312	2.0691	4.9367	2.082

Table 2 and 3. In the PSO tuned GMC, the following values are assigned: dimension is set to two; PSO parameters are set to $C_1 = 0.12$, $C_2 = 1.2$; its momentum has the value of 0.9 and the Integral Square Error (ISE) is used to converge the algorithm.

Table 3: BF-PSO tuned GMC parameters

	Time interval (0-40) min		Time interval (40-80) min		Time interval (80-120) min	
Number of iterations (Bacteria)	K_1	K_2	K_1	K_2	K_1	K_2
10	4.8514	1.2276	4.8839	1.1144	5.7567	0.6733
20	4.835	1.1109	5.2407	1.035	5.8409	0.911
30	4.8759	1.0963	5.2025	1.7841	5.5816	1.1137
40	4.8242	1.6079	4.8448	1.2100	5.8959	0.8787
50	4.9154	1.3669	5.2882	1.2872	5.3933	1.1326
60	4.8961	0.9508	4.8992	1.1941	5.2351	1.6008
70	4.8240	0.8662	4.7949	0.9699	5.1332	1.8222
80	4.8665	1.1435	4.8499	1.2125	5.2616	1.4794
90	4.9515	1.7238	4.9024	1.1224	5.1705	1.9831
100	4.9423	1.3155	4.9290	1.6254	5.1494	1.9251
120	4.3184	0.4045	4.9666	1.383	5.1656	1.9045
150	4.3627	0.4429	4.8957	1.3258	5.1554	1.9067

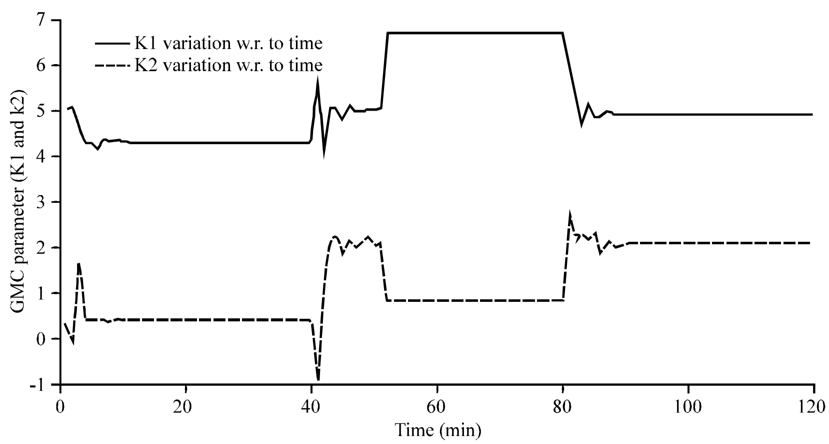

Fig. 5: PSO tuned GMC parameters variation with respect to three switching time intervals

From Table 2 the variation of number of swarms means the change in number of iterations, while increasing the number of iterations, the PSO settles in an optimized value of GMC controller parameters i.e. K_1 and K_2 are settled for the three different switching time intervals (0-40, 40-80, 80-120) are shown in Fig. 5.

This optimized GMC tuning parameters are integrated in the controller with each time interval, it is adapted and the simulated response of the batch reactor for this controller setting has been revealed in Fig. 6a and b.

In the BF-PSO based GMC tuning, the following values are assigned:

- Search space dimension is two; number of chemotactic steps are set to ten; length of swim is four; number of reproduction steps are four; number of elimination dispersal event is two; number of bacteria reproduction per generation is half of the number of bacteria; probability of bacteria elimination has a value of 0.25

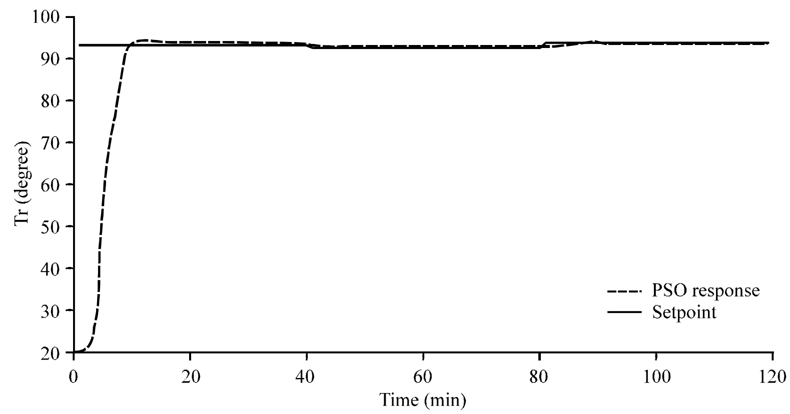

Fig. 6a: PSO tuned GMC Response

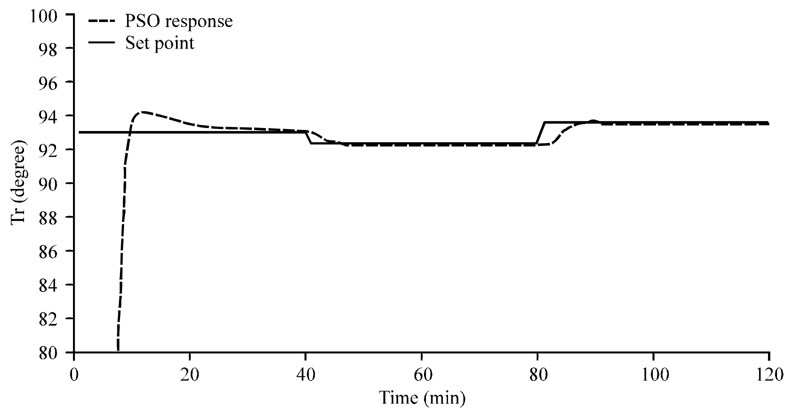

Fig. 6b: PSO tuned GMC Response (Magnified view of the above figure)

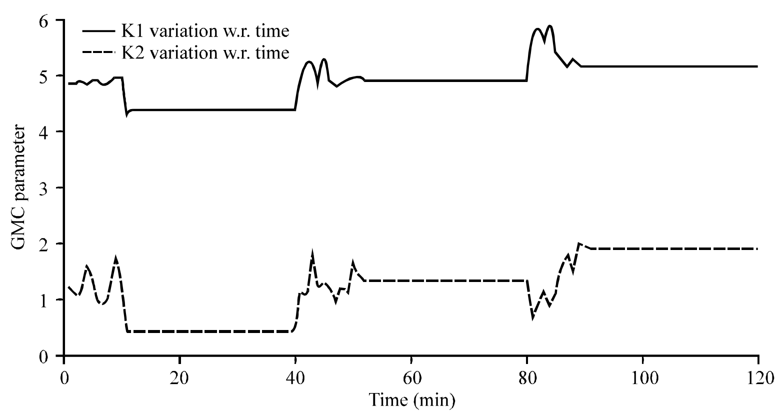

Fig. 7: BF-PSO tuned GMC parameters Variation with respect time intervals

From the Table 3, the increased number of bacteria makes the iteration changes and the controller values are settled in each time interval as shown in Fig. 7.

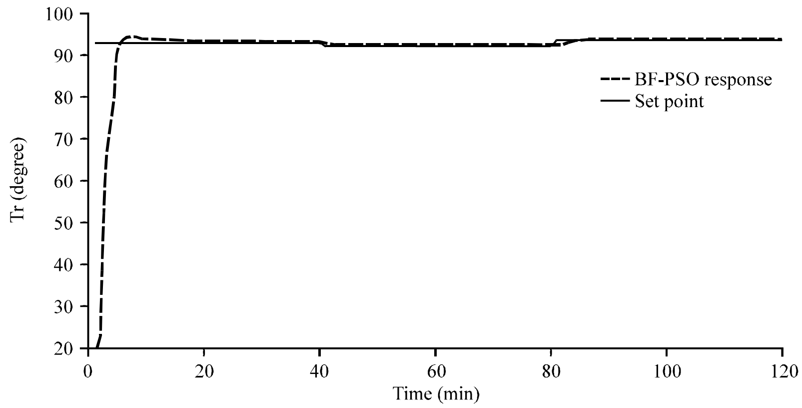

Fig. 8a: BF-PSO tuned GMC response

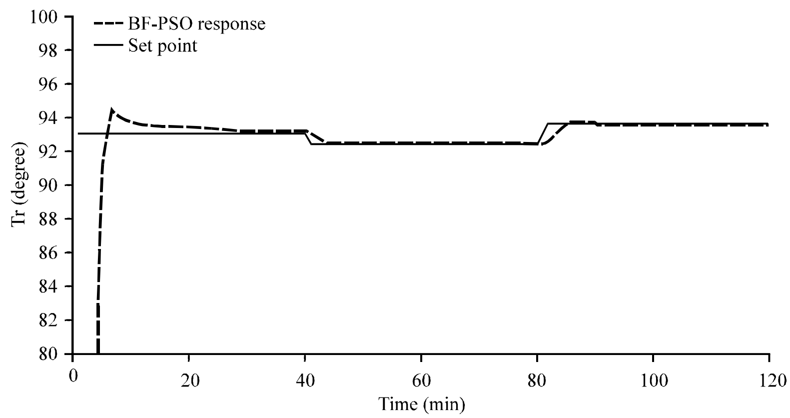

Fig. 8b: BF-PSO tuned GMC response (in magnified view)

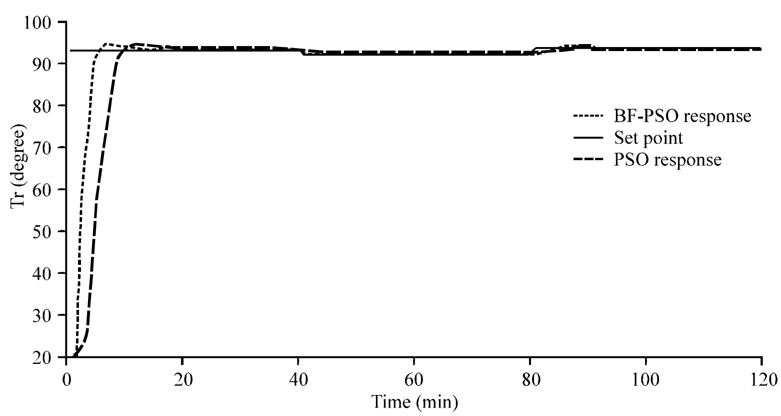

Fig. 9a: Comparison of PSO and BF-PSO tuned GMC response

The response of the integrated BF-PSO tuned GMC for the batch reactor with three switching interval is simulated with the process and shown in Fig. 8a and b.

BF-PSO response produce fast rise time and to reach its set point at time t = 5 min and giving good tracking over the multiple set points than PSO which has rise time t = 10 min as shown in Fig. 9a and b.

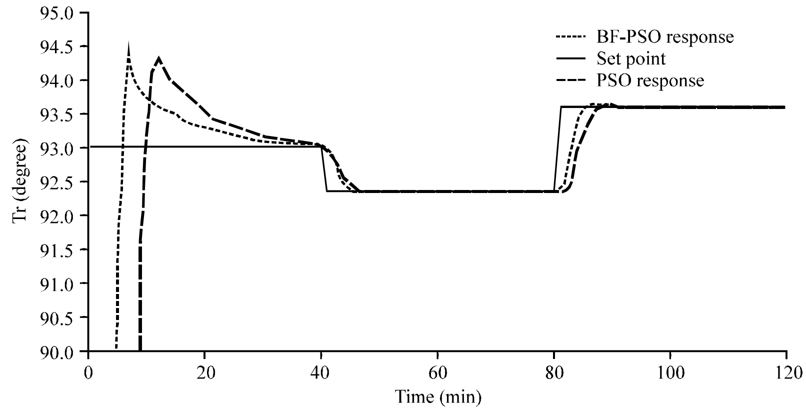

Fig. 9b: Comparison of PSO and BF-PSO tuned GMC response (in magnified view)

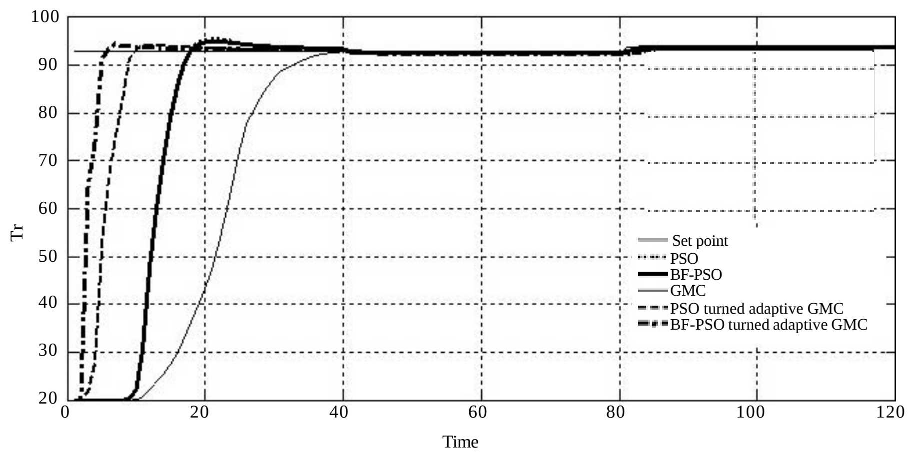

Fig. 10a: Comparison of proposed controller with single tuned and common GMC

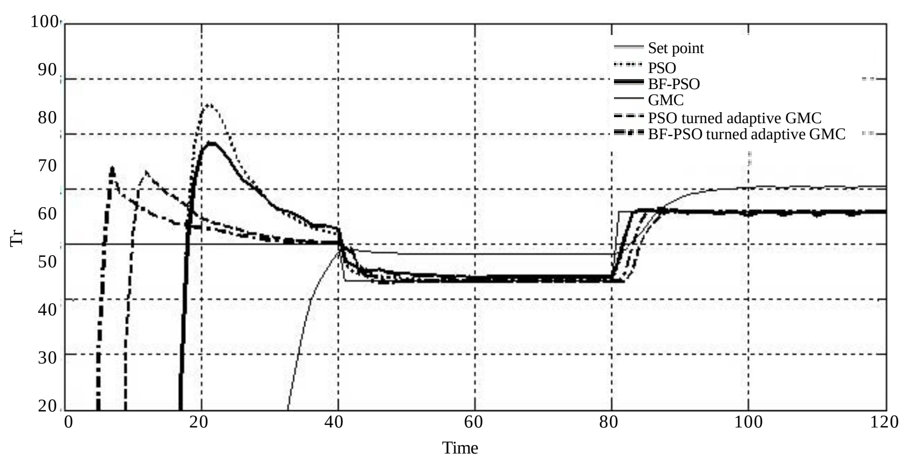

Fig. 10b: Comparison of proposed controller with single tuned and common GMC (in magnified view)

Table 4: Controller evaluation

		Optimum settings		Performance criteria	
S. No.	Controllers	K_1	K_2	ISE	IAE
1	GMC	0.12	0.0001	21870	619.3
2	PSO single tuned GMC	4.3393	0.3086	1628	80.93
3	BF-PSO single tuned GMC	4.3762	0.3225	1529	76.75
4	PSO gain scheduled GMC				
	(0-40) min	4.3117	0.3993	612.4	30.067
	(40-80) min	5.0312	2.0691	0.0333	0.1933
	(80-120) min	4.9367	2.082	0.1476	0.4063
5	BF-PSO gain scheduled GMC				
	(0-40) min	4.3627	0.4429	605.3	30.02
	(40-80) min	4.8957	1.3258	0.0332	0.1856
	(80-120) min	5.1554	1.9067	0.1413	0.3956

The proposed controller performance compared with the nominal GMC setting, the single tuned GMC based on PSO and BF-PSO techniques and gain scheduled GMC based on PSO and BF-PSO with its performance measure as Integral Square Error (ISE), Integral Absolute Error (IAE) are presented in the Table 4.

The performance of gain scheduled GMC based on BF-PSO is better than the other controller responses as shown in Fig. 10a and b and also the performance criteria ISE and IAE are good for the BF-PSO based gain scheduled GMC controller.

CONCLUSION

Swarm intelligent techniques are popularly used for tuning of PID controller nowadays. These techniques developed from replicating the evolutionary process and the behaviours of biology with basic mathematical operations. Therefore, they are simple and easy to be implemented. And also they don't insist to meet the state of differentiability, convexity and other conditions for mathematical description of the problem. Here, PSO and BF-PSO tuning has been attempted to tune Generic Model controller (GMC) parameters for tracking the optimal reactor temperature profile to the batch reactor. The simulation results presented shows the betterness of the hybrid optimization method validated which replicates the efficiency of the BF-PSO in terms of time domain specifications. It is also observed that BF-PSO based gain scheduled GMC i.e., as per the optimal temperature profile the set point is varying with three switching time interval; so the GMC parameters are also optimized in these three switching interval, and the integrated response of this gain scheduled adaptive GMC has produced minimum performance index ISE and IAE with improved responses for multiple set point tracking and also in terms of time domain specifications. Further, the work can be applied for the complex process also by including disturbances.

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