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Multi Objective Optimization of Multi Component Isothermal Liquid-Phase Kinetic Sequence using Multivariable PI Control

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Abstract

In this paper, an optimal tuned saturated PI type controller with anti-windup structure is used for process control. In first step, a single objective genetic algorithm is used to find the optimal values of controller parameters. To show the difference between optimal and non-optimal control, we use this controller to track the square pulse. The results show that by choosing the control parameters randomly the output cannot track the reference signal but by optimizing the control parameters, the error, and settling time decreases significantly and efficiency of control increases but it needs more control effort. To find the optimal control parameters with lower control input, a multi objective genetic algorithm is used in next step and three points in Pareto front are analysed. It is shown that this method increases the control efficiency and needs lower control input than obtained by single objective genetic algorithm.

Keywords: *multi objective optimal process control, GA algorithm, multi component isothermal liquid-phase kinetic sequence, multivariable saturated Sliding mode PI control*

1. Introduction

In the recent years, Control of chemical reaction procedure attract many researchers and they used different control methods to control the nonlinear manner of chemical reactions such as including feed-back linearization, sliding mode control, adaptive/neural control and nonlinear model predictive control [1], [2], [3], [4], [5]. Seshagiri and Khalil developed a new "conditional integrator" approach to the design of robust output regulation for multi-input multi-output (MIMO) minimum phase nonlinear systems transformable into the normal form, uniformly in a set of constant disturbances and uncertain parameters [6] and later they showed that this method tuned saturated PI/PID type controller with an anti-windup structure in some cases [7]. A genetic algorithm (GA) is an optimization technique that looks for the solution of the optimization problem, imitating species evolutionary mechanism [8], [9], [10], [11], [12]. In this type of algorithms, a set of individuals (so-called population) changes generation by generation (evolution) adapting better to the environment. Many multi-objective optimization algorithms using evolutionary concepts have been suggested since the pioneering work by Schaffer [13]. In order to obtain the best results, the search process needs to be guided toward the Pareto-optimal front, maintaining diversity to prevent premature convergence and to achieve a well distributed population.

In this paper we optimize the multivariable sliding mode PI control parameters for process control given in [7]. We use single objective genetic algorithm to optimize the error mean square used as objective function. The results show that optimizing control parameters results in high control input. To decrease the control input, a multi objective genetic algorithm is used when the maximum control input is defined as objective function. The results showed that optimizing the control parameters improve the control efficiency and reduces the error settling time in both cases. This paper is organized as follow: in section 2 the mathematical modeling of multi component isothermal liquid-phase kinetic sequence carried out in a continuous stirred-tank reactor (CSTR) is presented. In section 3, the control strategy for multi variable system is presented. Finally, section 4 shows the performances of the proposed optimal control obtained through simulation.

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2. Mathematical Modeling

The system involves the following multi component isothermal liquid-phase kinetic sequence carried out in a CSTR [9], [14], [15]. The nonlinear differential equations of system can be written as:

$$\begin{aligned} \dot{x}_1 &= 1-(1+D_{a1})x_1 + D_{a2}x_2^{\,2} \\ \dot{x}_2 &= -x_2 + (D_{a1})x_1 - D_{a2}x_2^{\,2} - D_{a3}x_2^{\,2} + u \\ \dot{x}_3 &= -x_3 + D_{a3}x_2^{\,2} \\ y &= x_3 \end{aligned} \tag{1}$$

Where

- x_1 : normalized concentration $C_A \,/ C_{AF}$ of a species A;
- x_2 : normalized concentration $C_B \,/ C_{AF}$ of a species B;
- x_3: normalized concentration $C_C \,/ C_{AF}$ of a species C;
- C_{AF} : feed concentration of the species A (mol.m^{-1});
- *u*: ratio of the per-unit volumetric molar feed rate of species B, denoted by N_{BF} , and the feed concentration C_{AF} , i.e. $u = N_{BF} \,/\, F\, C_{AF}$;
- *F*: volumetric feed rate (m^3 s^{-1});
- $D_{a1} = g_1 V \,/\, F$ constant parameter;
- $D_{a2} = g_2 V C_{AF} \,/\, F$ constant parameter;
- $D_{a3} = g_3 V C_{AF} \,/\, F$ constant parameter;
- *V* : the volume of the reactor (m^3);
- g_1, g_2, g_3: first order rate constants (s^{-1}).

3. Control Strategy

For a SISO system, multivariable PI controller can be simplified as following equations. To see more details about how this simplification has been done see [15]

$$\dot{\sigma} = -k_0\sigma + \mu \ \mathrm{sat}\left(\frac{k_0\sigma + k_1 e_1 + k_2 e_2}{\mu}\right) \tag{2}$$

$$u = -\mu \ \mathrm{sat}\left(\frac{k_0\sigma + k_1 e_1 + k_2 e_2}{\mu}\right) \tag{3}$$

where

$$e_1 = x_3 - \overline{y}, \qquad e_2 = \dot{e}_1 = -x_3 + D_{a3}x_2^{\,2}, \qquad z = x_1 - \overline{x_1} \tag{4}$$

The parameter μ result from replacing an ideal SMC with its continuous approximation, and hence should be chosen “sufficiently small” to recover the performance of the ideal SMC. Similarly, in order for the output feedback controller to recover the performance under state feedback. Therefore, one might view μ as tuning parameters and reduce it gradually until the transient response under partial state feedback is close enough to the ideal SMC. k_0 , k_1 and k_2 are control parameters and in this paper we will optimize to increase controlling efficiency.

4. Optimization and Simulation

To find the optimal values of parameters k_0, k_1 and k_2 we use Genetic Algorithms. A brief overview of how a genetic algorithm works is described below: First, a number of individuals (the population) are randomly initialized. The objective function is then evaluated for these individuals, producing the first generation of genomes. If the optimization criteria are not met, the creation of a new generation starts Individuals are selected according to their fitness for the production of offspring. Parents are recombined (crossover) to produce offspring. All offspring will be mutated with a certain probability. The fitness of the offspring is then computed. The offspring are inserted into the population replacing the parents, producing a new generation.

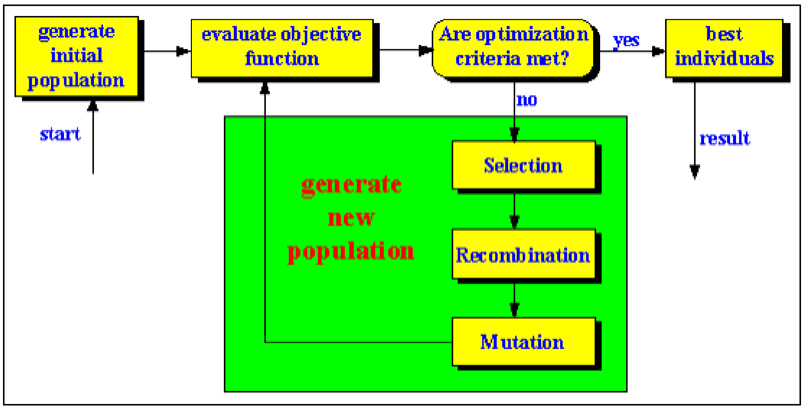

Figure 1. GA Flowchart

This cycle is performed until the optimization criteria are reached, or until a pre-set maximum number of generations have been generated. The initially and randomly selected population is left to evolve for 30 generations, after which no significant change is found in the objective function value. So this is used as termination criteria for the algorithm [16]. Twelve-bit string element is used for the encoding of each of the controller parameters. The crossover and mutation probabilities are chosen to be 0.8 and 0.02, respectively. The genetic algorithm MATLAB toolbox developed by Chipperfield [17] (available freely on the web) was used in the present study. The mean squared normalized error is considered as objective function in this section. The lower and upper bounds of optimization parameters are set as $0 < k_0, k_1, k_2 < 50$. To show the effectiveness of optimizing the control parameters, we try to track the signal plotted in Figure 2.

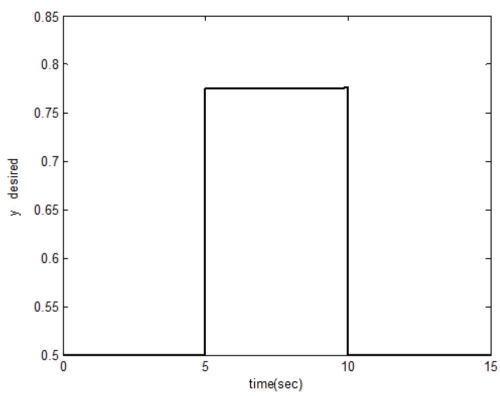

Figure 2. Desired Signal

To compare the optimal parameter effect on control, simulation is run for one random situation as: $k_0 = 1, k_1 = 5, k_2 = 2$. Figure (3) shows the fitness value as a function of generation. Black point is the best fitness value of populations in any generation and blue point is the mean of all individual's fitness value in generations. As seen in this figure, mean value converges to the best value after 10 generations and the best fitness value is 0.0022. The parameters assumed to be $D_{a1} = 3$, $D_{a2} = 0.5$ and $D_{a3} = 1$.

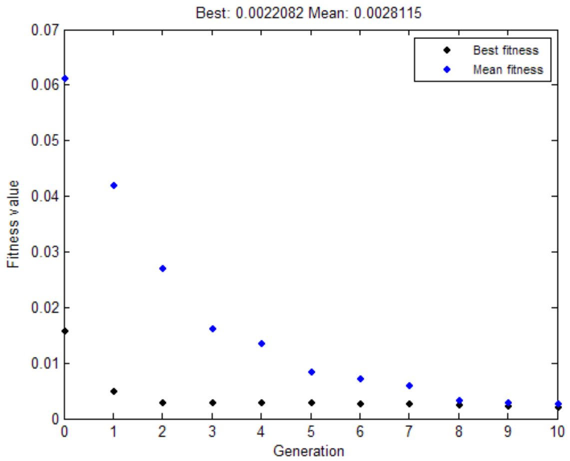

Figure 3. Optimization procedure

The response of the system for optimal parameters and non-optimal parameters are shown in Figure 4. As seen in this figure, by optimizing of control parameters, the tracking error set to zero in shorter time than non-optimized parameter system.

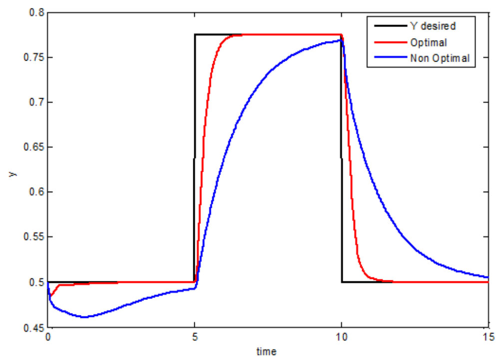

Figure 4. Time response of y for optimal and non-optimal parameters

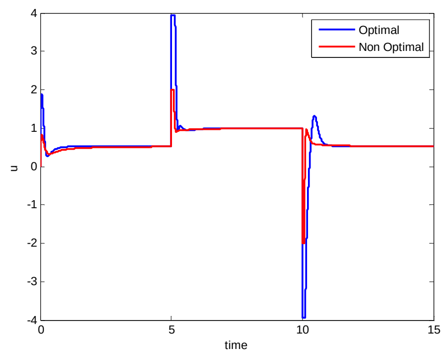

Figure 5. Control input for optimal and non-optimal parameters

To see the control effort for optimal and non-optimal control system, the control effort is plotted for both cases in Figure 5. As seen in this figure, the control effort for optimal parameters is larger than non-optimal situation. To reduce the amplitude of control input, we use multi objective optimization in next step and introduce Mean squared normalized error and maximum value of control effort as objective functions.

A single objective optimization algorithm will normally be terminated upon obtaining an optimal solution. However, for most realistic the multi-objective problems, there could be a number of optimal solutions. Suitability of one solution depends on a number of factors including user's choice and problem environment, and hence finding the entire set of optimal solutions may be desired. Mathematically, a general multi objective optimization problem contains a number of objectives to be minimized and (optional) constraints to be satisfied. In this case, a multi objective optimization problem consists of minimizing a vector of functions $F(x) = (f_1(x), f_2(x), ..., f_n(x))$ subject to $x \in X$.

The functions, $f_1, f_2, ..., f_n$, usually in conflict with each other, are a mathematical description of the performance criteria. The meaning of optimum is not well defined in this context, so it is difficult to have a vector of decision variables that optimizes all the objectives simultaneously. Therefore, the concept of Pareto optimality is used. The concept of optimality in single objective is not directly applicable in multi objective optimization problems. For this reason a classification of the solutions is introduced in terms of Pareto optimality, according to the following definitions [16].

In terms of minimization of objective functions:

Definition 1. Pareto dominance: An element $x \in X$ is called a feasible solution. A feasible solution x_1 is said to dominate another feasible solution x_2 (denote this relationship by $x_1 > x_2$) if

$$f_i(x_1) \le f_i(x_2),\ \forall i \in \{1,2,...,n\},\ \wedge\ \exists j \in \{1,2,...,n\} : f_j(x_1) < f_j(x_2) .$$

Definition 2. Pareto optimal solution: A solution vector $x^* \in X$ is a Pareto optimal solution if

$$\neg\exists x \in X : f_i(x) \le f_i(x^*),\ \forall i \in \{1,2,...,n\}\ \wedge\ F(x) \ne F(x^*) .$$

These solutions are also called true Pareto solutions.

Definition 3. Pareto set: A set of non-dominated feasible solutions $\{x^* \mid \neg\exists x \in X : x > x^*\}$ is said to be a Pareto set.

Definition 4. Pareto front: The set of vectors in the objective space that are image of a Pareto set, is called Pareto front, i.e.

$$\{F(x^*) \mid \neg\exists x \in X : x > x^*\}$$

A representation of the Pareto front for a bi-objective space is presented in Figure 5.

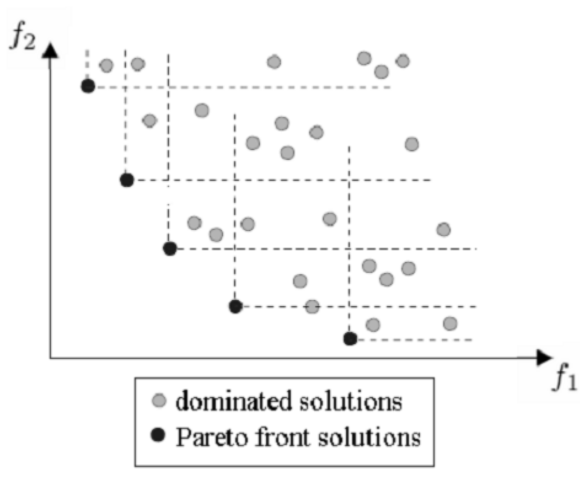

Figure 6. The Pareto front of a set of solutions in a bi-objective space

Figure (7) shows the Pareto front of multi objective optimization of the system. X-axis is error mean square and y-axis is maximum of control input. The points in this figure are non-dominated points and the optimal parameters can be chosen according to design condition. For example 3 points are selected in Table 1 and the response of the system and control input according to these 3 points are plotted in Figure 8 and Figure 9.

Table1. Three point in the Pareto front Figure 7.

	K1	K2	K3	Norm(error)	Max(u)
Point1	4.381335	1.742179	2.898208	0.002438	2.898208
Point2	4.068798	2.081135	1.867676	0.003143	1.867676
Point3	2.728759	2.472861	0.760033	0.011705	0.760033

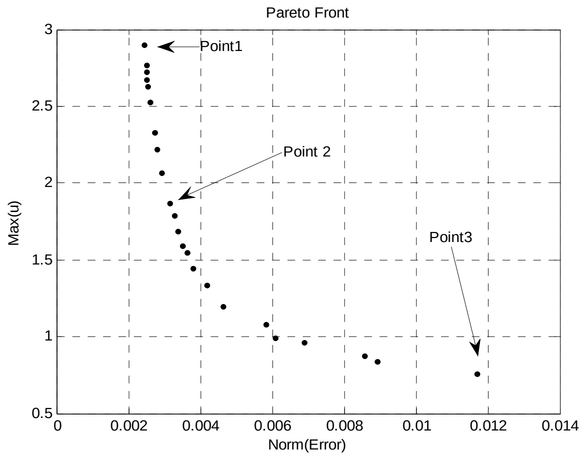

Figure 7. Pareto Front

Time response of y is plotted in Figure 8. As seen in this figure, by choosing point1, settling time of error decreases but as seen in Figure 9, it needs larger control input. If the control input is restricted to 2 for example, point 2 can be selected. As seen in Figure 8 the time response of this point is good and it is obvious from Figure 9 that the maximum control input is lower than 2.

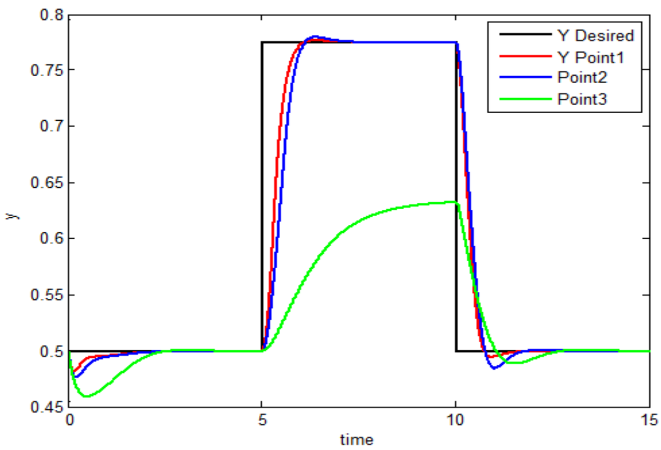

Figure 8. Time response of y for optimal and non-optimal parameters

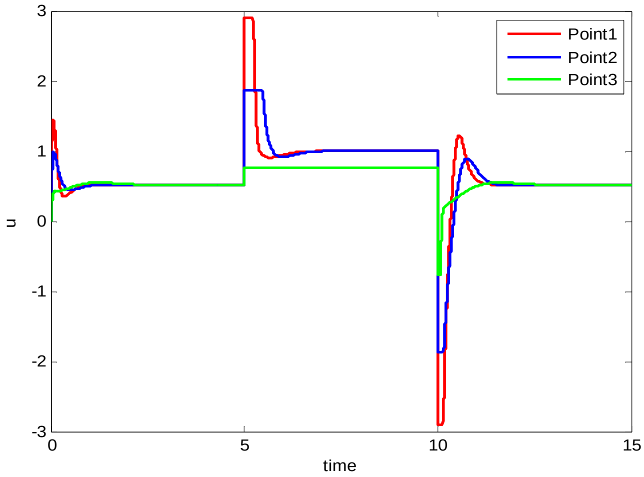

Figure 9. Control Input for 3 points selected in Figure 7

5. Conclusion

In this paper we optimize the sliding mode Multivariable PI Control parameters for process control. We use single objective genetic algorithm to optimize the control parameters and Error mean square is used as objective function. The results show that by optimizing control parameters result to high control input. To decrease the control input, multi objective genetic algorithm is used and the maximum amount of control input is defined as another objective function. The results showed that optimizing the control parameters improve the control efficiency and reduces the error settling time in both cases and another advantage of this method is the opportunity to select best point considering the input constraints.

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