# Fed-Batch Cultivation Control Based on Genetic Algorithm PID Controller Tuning

Olympia Roeva[1] and Tsonyo Slavov[2]

[1] Centre of Biomedical Engineering - BAS, Bulgaria
olympia@clbme.bas.bg
[2] Technical University - Sofia, Bulgaria
ts_slavov@tu-sofia.bg

**Abstract.** In this paper a universal discrete PID controller for the control of *E. coli* fed-batch cultivation processes is designed. The controller is used to control feed rate and to maintain glucose concentration at the desired set point. Tuning the PID controller, to achieve good closed-loop system performance, using genetic algorithms is proposed. As a result the optimal PID controller settings are obtained. For a short time the controller sets the control variable and maintains it at the desired set point during the process. Application of the designed controller provides maintaining of the accuracy and efficiency of the system performance.

## 1 Introduction

A number of processes in the biochemical industry are controlled using PID (proportional-integral-derivative) controllers. Until now commercially available controllers exist only for well established measurement systems as per pH, temperature, stirrer speed, dissolved oxygen etc. The reason for this is highly changing dynamics of most bioprocesses, which is caused by the non-linear growth of the cells, the metabolic changes as well as changes in the overall metabolism. That is, since the PID controller is usually poorly tuned. A higher degree of experience and technology are required for the tuning in a real plant. Tuning a PID controller appears to be conceptually intuitive but can be hard in practice, if complex systems, as cultivation processes are considered. Due to a change of the system parameters, the conventional PID controllers result in sub-optimal corrective actions and hence require retuning. This stimulates the development of tools that can assist engineers to achieve the best overall PID control for the entire operating envelope of a given process. While for control of continuous cultivation processes the controller tuning could be done with traditional methodology, as it is presented in [8], for fed-batch cultivation processes such methodologies could not be applied. For the quality controller tuning optimization methods could be applied, although the tuning procedure is a big challenge for the conventional optimization methods. As an alternative to overcome the controller tuning difficulties various metaheuristics, for example genetic algorithms (GA), could be used [8,5].

I. Dimov, S. Dimova, and N. Kolkovska (Eds.): NMA 2010, LNCS 6046, pp. 289–296, 2011.

This paper focuses on an optimal tuning of universal digital PID controller for control of an *E. coli* fed-batch cultivation process. To achieve good closed-loop system performance GA based controller tuning is proposed. The GA are highly relevant for industrial applications, because they are capable of handling problems with non-linear constraints, multiple objectives, and dynamic components - properties that frequently appear in the real-world problems [8]. Since its introduction and subsequent popularization [4], the GA has been frequently utilized as an alternative optimization tool to the conventional methods [9].

The paper is organized as follows: theoretical background of the GA and of the control algorithm are presented respectively in Section 2 and Section 3. The considered *E. coli* cultivation process is described in Section 4. Controller tuning problem is formulated in Section 5. The results and discussion are presented in Section 6. Conclusion remarks are done in Section 7.

## 2 Background of the Genetic Algorithms

Genetic algorithms are a class of non-gradient methods. The basic idea of GA is the mechanism of natural selection. Each optimization parameter, $x_n$, is coded into a gene as for example a real number or string of bits. The corresponding genes for all parameters, $x_1, ..., x_n$, form a chromosome, which describes each individual. Each individual represents a possible solution, and a set of individuals form a population. In a population, the fittest are selected for mating. Mating is performed by combining genes from different parents by crossover to produce a child. Solutions are also "mutated" by making a small change to a single element of the solution. Finally the children are inserted into the population and the procedure starts over again. The optimization continues until the end-condition is satisfied.

*Initial population:* A GA starts with a population of strings to be able to generate successive populations of strings afterwards. The initialization is usually done randomly. *Evaluation*: After every generated population, the individuals of the population must be evaluated to be able to distinguish between good and bad individuals. This is done by mapping the objective function to a "fitness function": a non-negative figure of merit. *Reproduction*: An important aspect is to decide, which individuals should be chosen as parents for the purpose of procreation. With GA, this selection is based on the string fitness: according to the "survival of the fittest" principle. *Recombination*: Once two parents have been selected, the GA combines them to create two new offspring using crossover operator. The role of the crossover operator is to allow the advantageous traits to be spread throughout the population in order that the population as a whole may benefit from this chance discovery [9]. The crossover is the prime distinguishing factor of a GA from other optimization algorithms. *Mutation*: The last operator is the mutation algorithm. The effect of mutation is to reintroduce divergence into a converging population. The biological inspiration behind this operator is the way in which a chance mutation in a natural chromosome can lead to the development of desirable traits giving the individuals advantageous characteristics over its competitors [9].

A pseudo code of a GA is presented as:

| | |
|---|---|
| $i = 0$ | set generation number to zero |
| initpopulation $P(0)$ | initialize a usually random population of individuals |
| evaluate $P(0)$ | evaluate fitness of all initial individuals of population |
| while (not done) do | test for termination criterion (time, fitness, etc.) |
| begin | |
| $i = i + 1$ | increase the generation number |
| select $P(i)$ from $P(i-1)$ | select a sub-population for offspring reproduction |
| recombine $P(i)$ | recombine the genes of selected parents |
| mutate $P(i)$ | perturb the mated population stochastically |
| evaluate $P(i)$ | evaluate its new fitness |
| end | |

## 3 Background of the Control Algorithm

A PID controller is a generic control algorithm widely used in industrial control systems. The controller parameters used in the calculation must be tuned according to the nature of the system. The standard PID controller calculation (algorithm) involves three separate modes; the proportional (P), the integral (I) and derivative (D). The P mode determines the reaction to the current error, the I mode determines the reaction based on the sum of recent errors, and the D mode determines the reaction based on the rate at which the error has been changing. The weighted sum of these three actions is used to adjust the process via a control element.

In this paper a universal digital PID controller is used due to unsatisfactory performance of control system based on a standard PID controller. A typical structure of a PID control system is shown in Fig. 1. The error signal $e(t)$ is used to generate the P, I, and D modes, with the resulting signals weighted and summed to form the control signal $u(t)$ applied to the plant model. Introducing coefficients $b$, $c$ and a first-order low pass filter in D mode leads to a negligibly more complex controller, but significantly improves the control system's performance. The coefficient $b$ ($b \leq 1$) is used to weight out the $r(t)$ in P mode of controller and the coefficient $c$ ($c \leq 1$) is used to weight out the $r(t)$ in D mode of the controller. Typically in industrial applications $b$ and $c$ are chosen to be equal to 0 or 1. Using of a first-order low pass filter reduces the influence of measurement noise. In real applications discrete time PID controller is implemented. Many formal techniques for discretization exist [7]. In this paper backward Euler method is used [6]. The mathematical description of discrete-time universal PID controller is:

$$u(k) = u_p(k) + u_i(k) + u_d(k), \tag{1}$$

$$u_p(k) = K_p(br(k) - y(k)), \tag{2}$$

$$u_i(k) = u_i(k-1) + b_{i1}(r(k) - y(k)) + b_{i2}(r(k-1) - y(k-1)), \tag{3}$$

$$u_d(k) = a_d u_d(k-1) + b_d(cr(k) - cr(k-1) - y(k) + y(k-1)), \tag{4}$$

where $k$ is the number of sample, $u(k)$ - control signal, $u_p(k), u_i(k)$ and $u_d(k)$ - proportional, integral and derivative modes of control signal, $r(k)$ - reference signal, $y(k)$ - output signal, $K_p$ - proportional gain, $T_i$ - integral time, $T_d$ - derivative time, $T_d/N$ - time constant of first-order low pass filter, $T_0$ - sample time, $b$ and $c$ - weighting coefficients, $b_{i1} = K_p \frac{T_0}{T_i}$, $b_{i2} = 0$, $a_d = \frac{T_d}{T_d + NT_0}$, $b_d = K_p \frac{T_d N}{T_d + NT_0}$.

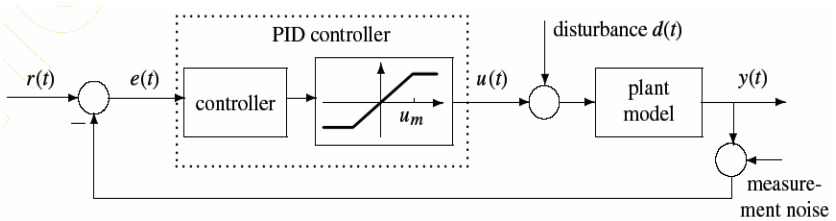


**Fig. 1.** A typical structure of a PID control system

By tuning the constants ($K_p, T_i, T_d, b, c$ and $N$) in the PID controller algorithm, the controller can provide control action designed for specific process requirements. Two general tuning methods were proposed by Ziegler and Nichols [11] and have been widely utilized either in the original form or in modified forms. These methods, referred to as "classical" tuning methods, determine the PID parameters using empirical formulae [2,3]. These methods are inapplicable to the considered here non-linear control system. The regarded fed-batch cultivation process can not to be linearized around an equilibrium point of a system. In this case there is no equilibrium point. If a linear approximation is found, the resulting model will be valid only for a small region around the linearization point. The controller tuned using this linear model will work properly only for this limited region. Therefore, it is necessary to use non-classical tuning methods to achieve the best overall PID control for the entire operating envelope of the given system.

## 4 *E. coli MC4110* Fed-Batch Cultivation Model

Fed-batch cultivation process of *E. coli MC4110* is considered. The cultivation conditions and data measurements are discussed in [1]. The mathematical model can be represented by the following dynamic mass balance equations [1]:

$$\frac{dX}{dt} = \mu_{max} \frac{S}{k_S + S} X - \frac{F}{V} X \tag{5}$$

$$\frac{dS}{dt} = -\frac{1}{Y_{S/X}} \mu_{max} \frac{S}{k_S + S} X + \frac{F}{V}(S_{in} - S) + \xi \tag{6}$$

$$\frac{dV}{dt} = F \tag{7}$$

where $X$ is the biomass concentration, [g/l]; $S$ - substrate (glucose) concentration, [g/l]; $F$ - feeding rate, [l/h]; $V$ - bioreactor volume, [l]; $S_{in}$ - substrate concentration in the feeding solution, [g/l]; $\mu_{max}$ - maximum value of the specific growth rate, [$h^{-1}$]; $k_S$ - saturation constant, [g/l]; $Y_{S/X}$ - yield coefficient, [-], $\xi$ - measurement noise. Numerical values of the model parameters used in simulations are according to [1]: $\mu_{max} = 0.55\ h^{-1}$, $k_S = 0.01$ g/l, $Y_{S/X} = 0.50$.

## 5 PID Controller Tuning Using Genetic Algorithm

The simple GA is a powerful tool that is able to converge rapidly to an optimum of many different objective functions. The user has to create a code scheme, a fitness function and implement these into the GA, which mechanisms are easy to implement into a computer program. The optimal value of the PID controller parameters ($K_p, T_i, T_d, b, c$ and $N$) is to be found using GA.

*Initialization of algorithm parameters:* The most appropriate GA parameters and operators, based on previous author's investigations on the effects of the different GA parameters on the outcome of the GA [10] are used.

*Representation of chromosomes*: Representation of chromosomes is a critical part of the GA application. In order to use the GA to identify controller parameters, it is necessary to encode the parameters in accordance with the method of concatenated, multiparameter, mapped, fixed-point coding [4]. Here, a chromosome is a sequence of $m$- parts each of them with $\mathbf{n}$ (encoding precision) genes. In the case of tuning the three controller parameters - $K_p$, $T_i$ and $T_d$, the chromosome is a sequence of three parts. In the case of tuning of all the defined parameters - $K_p, T_i, T_d, b, c$ and $N$, the chromosome is a sequence of six parts. The range of the tuning parameters is considered as follows: $K_p \in [0, 2]$, $T_i \in [0, 1]$, $T_d \in [0, 0.1]$, $b \in [0, 1]$, $c \in [0, 1]$ and $N \in [0.001, 1000]$. After several runs the range for the parameters is specified to: $K_p \in [0.4, 2]$, $T_i \in [0.005, 1]$ and $T_d \in [0.003, 0.1]$.

Following a random initial choice, entire generations of such strings are readily processed in accordance with the basic genetic operators of selection, crossover and mutation. In particular, the selection process ensures that the successive generations of PID controller parameters produced by the GA exhibit progressively improving behavior with respect to some fitness measure.

*Objective function:* To evaluate the significance of the tuning procedure and controller performance four criteria are used - integrated squared error ($I_{ISE}$); integrated absolute error ($I_{IAE}$); integrated time-weighted absolute error ($I_{ITAE}$) and integrated squared time-weighted error ($I_{ISTE}$):

$$I_{ISE} = \sum_{k=0}^{M} e(k)^2,\ I_{IAE} = \sum_{k=0}^{M} |e(k)|,\ I_{ITAE} = \sum_{k=0}^{M} ke(k)^2,\ I_{ISTE} = \sum_{k=0}^{M} k^2 e(k)^2,$$

where the error $e$ is the difference between the set-point and the estimated substrate concentration ($S_{sp} - S$), $M$ - end sample of the cultivation.

*Termination criteria:* Here the termination criterion is considered to be the maximum number of generations. The chosen maximum number of generations is sufficient for reaching a satisfactory fitness value.

## 6 Results and Discussion

In the case of cultivation processes control the usual practice is to select PI or PID mode. A P controller reduces error but does not eliminate it, i.e. an offset between the actual and desired value will normally exist. The additional I mode corrects the error that occur between the desired value and the process output. Inclusion of the I mode makes the control system more likely to be oscillatory. Inclusion of the D mode (i.e. selecting PID mode) improves the speed of the responses, and consequently served to suppress the influence of the disturbance more strongly. However, the D mode functions are effective only when the controller parameters are tuned appropriately. Controller tuning is a subjective procedure and is certainly process dependent. For the considered here process the problem is to find a feed rate profile to establish small glucose concentration preventing the accumulation of growth inhibiting metabolites.

Using the considered four objective functions a series of test are performed. To obtain more realistic tests of the controller robustness and of the tuning procedure performance measurement noise is introduced in the simulation - white Gaussian zero mean noise with a variance 0.002 $g^2/l^2h$. For each criterion (in case of noise absence and in case of noise introducing) at least 35 runs of GA are performed. The controller parameters' tuning is performed for two cases: *Case 1* - tuning of the basic PID parameters - $K_p, T_i$ and $T_d$ (parameters $b$, $c$ and $N$ are defined as constants - $b = c = 1$, $N = 1000$) and *Case 2* - tuning all the six parameters. The results presented here are mean values of the all runs for the current case. The algorithm produces the same estimations with more than 80% coincidence. Some of the results from the GA application for PID tuning are presented in Table 1. The case with the introduction of noise is shown. This is more real case of the problem decision and the discussion of the corresponding results is more useful.

**Table 1.** Controller parameters, mean value (with noise)

| Case study | $K_p$ | $K_i$ | $K_d$ | $b$ | $c$ | $N$ | $I$ value |
|---|---|---|---|---|---|---|---|
| 1 | 0.4003 | 0.9846 | 0.0030 | 1.0000 | 1.0000 | 1000.0000 | $I_{ISE}$=16.1639 |
| 2 | 0.4041 | 0.9465 | 0.0030 | 0.9392 | 0.8709 | 778.3171 | $I_{ISE}$=16.1510 |
| 1 | 0.4002 | 0.9853 | 0.0030 | 1.0000 | 1.0000 | 1000.0000 | $I_{IAE}$=38.2181 |
| 2 | 0.4072 | 0.9356 | 0.0030 | 0.8375 | 0.9283 | 616.3588 | $I_{IAE}$=38.1324 |
| 1 | 0.4002 | 0.9874 | 0.0030 | 1.0000 | 1.0000 | 1000.0000 | $I_{ITAE}$=110.4505 |
| 2 | 0.4036 | 0.9353 | 0.0030 | 0.9036 | 0.9060 | 733.9115 | $I_{ITAE}$=110.3550 |
| 1 | 0.4002 | 0.9783 | 0.0030 | 1.0000 | 1.0000 | 1000.0000 | $I_{ISTE}$=755.1833 |
| 2 | 0.4035 | 0.9385 | 0.0030 | 0.8646 | 0.9370 | 537.9127 | $I_{ISTE}$=754.4549 |

The results show that all objective functions are representative and sophisticated controller performance indices. The obtained numerical values of the controller parameters for the four criteria, respectively in *Case 1* and *Case 2* are quite similar. The considered objective functions reflect the performance of the PID controller in a similar way. It could not define the best criterion.

As a result of the GA tuning the optimal PID controller settings are obtained. In Fig. 2 some results of controller and process performance are presented concerning *Case 2* and $I_{ITAE}$ criterion. The obtained results are compared with the results from the controller design of the same cultivation process reported in [1]. In Fig. 2a biomass concentration during the process is displayed. In Fig. 2b and Fig. 2d substrate concentrations and resulting feed rate profiles are presented.

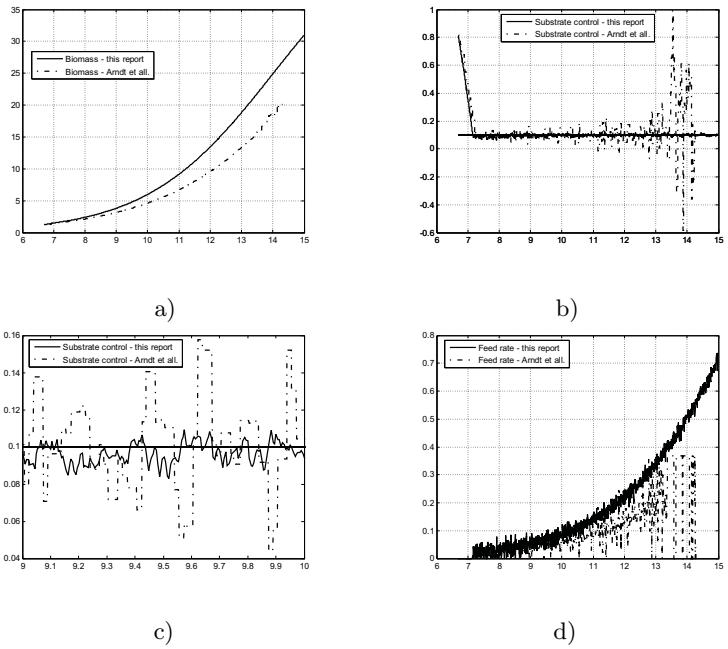


**Fig. 2.** Controller and process perfermance

For better visualization in Fig. 2c the substrate concentrations between 9 and 10 h from the cultivation for both studies (this and [1]) are presented. To show the stability of the controller designed here the cultivation process is simulated for a longer time period in comparison with [1]. As it can be seen for a short time the controller sets the control variable and keeps stable the glucose concentration at the set point of 0.1 g/l during the process. The maximum difference reported in [1] is 0.06 g/l and it has occurred in the second half of the process. In parallel, the maximum difference achieved here is 0.028 g/l. Here discussed controller has the better performance than the presented in [1]. The deviation from the setpoint is very small for the all time period. The resulting standard deviation and

mean value concerning control variable are: in this report $\rightarrow \sigma_s = 0.0063$ and $m_s = 0.0967$; in [1] $\rightarrow \sigma_s = 0.1513$ and $m_s = 0.1306$.

## 7 Conclusion

In the article are presented the results of a designed universal digital PID controller. The controller is used to control feed rate and to maintain glucose concentration at the desired set point for an *E. coli* fed-batch cultivation process. GA controller tuning to achieve good closed-loop system performance is proposed. Using four objective functions reflecting the performance of the PID controller, the significance of the tuning procedure is evaluated. As a result, the optimal PID controller settings are obtained. The presented results indicate high quality and better performance of the designed control system. For a short time the controller sets the control variable and maintains it at the desired set point during the cultivation process. It is demonstrated that the GA provide a simple, efficient and accurate approach to PID controllers tuning. Moreover, GA tuning can be regarded as an effective methodology for attaining improved performance of a process.

**Acknowledgements.** This work is partially supported by National Scientific Fund Grants DMU 02/4 and DID-02-29.

## References

1. Arndt, M., Hitzmann, B.: Feed Forward/feedback Control of Glucose Concentration during Cultivation of *Escherichia coli*. In: 8th IFAC Int. Conf. on Comp. Appl. in Biotechn., pp. 425–429 (2001)
2. Astrom, K., Hagglund, T.: PID Controllers, 2nd edn. Instr. Soc. of America (1995)
3. Garipov, E.: PID Controllers. Automatics and Informatics, 3 (2006) (in Bulgarian)
4. Goldberg, D.: Genetic algorithms in search, optimization and machine learning. Addison-Weslcy Publishing Company, Massachusetts (1989)
5. Gundogdu, O.: Optimal-tuning of PID Controller Gains using Genetic Algorithms. Journal of Engineering Sciences 11(1), 131–135 (2005)
6. Heath, M.T.: Computing, An Introductory Survey, 2nd edn. McGraw-Hill, New York (2002)
7. Kotsiantis, S., Kanellopoulos, D.: Discretization Techniques: A Recent Survey. GESTS Int. Transact. on Comp. Scien. and Eng. 32(1), 47–58 (2006)
8. Kumar, S.M.G., Jain, R., Anantharaman, N., Dharmalingam, V., Begum, K.M.M.S.: Genetic Algorithm Based PID Controller Tuning for a Model Bioreactor. Indian Chemical Engineer. 50(3), 214–226 (2008)
9. Parker, B.S.: Demonstration of using Genetic Algorithm Learning. Information Systems Teaching Laboratory (1992)
10. Roeva, O.: Improvement of Genetic Algorithm Performance for Identification of Cultivation Process Models. In: 9th WSEAS Int. Conf. on Evol. Comp., pp. 34–39 (2008)
11. Ziegler, J.G., Nichols, N.B.: Optimum Settings for Automatic Controllers. Trans. Amer. Soc. Mech. Eng. 64, 759–768 (1942)