Proceedings of the Federated Conference on
Computer Science and Information Systems pp. 455–462
ISBN 978-83-60810-51-4

Firefly Algorithm Tuning of PID Controller for Glucose Concentration Control during E. coli Fed-batch Cultivation Process

Olympia Roeva
Institute of Biophysics and Biomedical Engineering, BAS
105 Acad. G. Bonchev Str.,
1113 Sofia, Bulgaria
olympia@biomed.bas.bg

Tsonyo Slavov
Technical University of Sofia
8 Kliment Ohridski Bulv.
1000 Sofia, Bulgaria
ts_slavov@tu-sofia.bg

Abstract—**In this paper, a novel meta-heuristics algorithm, namely the Firefly Algorithm (FA), is applied to PID controller parameter tuning in Smith Predictor. 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. The FA adjustments are done based on several pre-tests. Simulation results indicate that the applied FA is effective and efficient. Good closed-loop system performance is achieved on the basis of the considered PID controllers tuning procedures. Moreover, the observed results are compared to the ones obtained by applying Genetic algorithms. The comparison of both meta-heuristics shows superior performance for FA PID controller tuning of the considered nonlinear control system than GA tuned controller.**

Keywords—meta-heuristics, firefly algorithm, genetic algorithm, E. coli cultivation process, PID controller, parameter tuning.

I. Introduction

Cultivation of recombinant micro-organisms, e.g. E. coli, in many cases is the only economical way to produce pharmaceutic biochemicals such as interleukins, insulin, interferons, enzymes and growth factors. To maximize the volumetric productivities of bacterial cultures, it is important to grow E. coli to high cell concentration. Among the different modes of operation, (batch, fed-batch and continuous), fed-batch operation is the most often used one in industry. Since both nutrient overfeeding and underfeeding is detrimental to cell growth and product formation, development of a suitable feeding strategy control is critical in fed-batch cultivation. The control strategy for substrate feed rate can be summarized in three groups: open (feedforward), closed-loop (feedback) control and mixed (feedforward-feedback). In feedback control of industrial cultivation processes, the proportional-integral-derivative (PID) controller is widely used [1, 2].

Usually the PID controller is poorly tuned due to highly changing dynamics of most bioprocesses caused by the nonlinear growth of the cells and the changes in the overall metabolism. The tuning procedure is a significant challenge for the conventional optimization methods. As an alternative, meta-heuristics could be applied [3-5].

During the last decade, a broad class of meta-heuristics has been developed and applied to a variety of areas. Algorithms like genetic algorithms and evolution strategies, ant colony optimization, artificial bee colony optimization, bacterial foraging algorithms, particle swarm optimization, tabu search, simulated annealing, multi-start and iterated local search are – among others – often listed as examples of classical meta-heuristics, and they have individual historical backgrounds and follow different paradigms and philosophies [6-9].

In the literature, there are results showing different strategies based on meta-heuristic algorithms for the optimal tuning of PID controllers. Results about application of simulated annealing and tabu search tuning considering linear systems are presented in [5, 10-14]. The properties of genetic algorithms (GA) result in increased use of this technique for tuning of PID controllers [3-4, 15-17]. Actually, there is a lack of results about using meta-heuristic algorithms for bioprocess control design, considering non-linear systems.

Recently, a new meta-heuristics called Firefly Algorithm (FA) has emerged. This algorithm was proposed by Xin-She Yang [18]. According to recent bibliography, the FA is very efficient and can outperform other meta-heuristics, such as genetic algorithms, in solving many optimization problems [18-21]. Although the FA has many similarities with other swarm intelligence based algorithms it is indeed much simpler in concept and implementation [20-21]. Based on bibliography results, it is evident that the FA is a powerful novel population-based method for solving optimization problems [22-25].

This paper aims to introduce for the first time an application of the FA specified to solve PID controller parameter tuning. An optimization algorithm based on FA is proposed for parameter tuning of the PID Controller for glucose concentration control of a nonlinear E. coli fed-batch cultivation process.

II. Problem Formulation

A modified Smith Predictor (SP) structure, proposed in [14], based on a nonlinear plant model is used here. When the object is characterized with a significant time delay, the conventional PID controller can not ensure the control system performance. A tool approved in the practice for time delay compensation is the SP [26]. In this predictor scheme, the mathematical model of the process is implemented in an internal feedback loop around a conventional controller. The major advantage of the SP is that delay issues can be ignored when designing the controller [27].

The structure of the control system is shown in Fig. 1. In the conventional case of SP, only the plant output is used to form the inner feedback. In this case, a universal PID controller is used to form the feedback term of control signal [14]. In addition, the process variables predicted by a nonlinear model are used to form the feedforward term of the control signal. This term is utilized to hold the nonlinear plant at the actual equilibrium point.

The block labeled "Nonlinear process model" predicts the non-delayed model output by equations:

$$\left|\begin{array}{l} \dot{\mathbf{x}}_m(t) = f_m(\mathbf{x}_m, F) + \boldsymbol{\eta}(t) \\ S_m(t) = \mathbf{H}\mathbf{x}_m(t) + \xi(t) \\ S_{CORm}(t) = S_m(t) + \dfrac{\mu_m(t) X_m(t)}{Y_{S/X}} \Delta t, \\ \mu_m(t) = \mu_{\max_m} \dfrac{S_m(t)}{k_S + S_m(t)} \end{array}\right. \tag{1}$$

$$\mathbf{x}_m(t) = \left[X_m(t) \quad S_m(t) \quad V_m(t)\right]^T \tag{2}$$

$$f_m(\mathbf{x}_m, F) = \left[\begin{array}{c} \mu_m(t) X_m(t) - \dfrac{F(t)}{V_m(t)} X_m(t) \\ -\dfrac{1}{Y_{S/X}} \mu_m(t) X_m(t) + \dfrac{F(t)}{V_m(t)} (S_{in} - S_m(t)) \\ F(t) \\ \end{array}\right] \tag{3}$$

$$\mathbf{H} = (0 \quad 1 \quad 0 \quad 0), \tag{4}$$

$$\boldsymbol{\eta}(t) = \left[\eta_{\gamma_X}(t) \quad \eta_{\gamma_S}(t) \quad 0 \quad \eta_{\mu_{\max}}(t)\right]^T, \tag{5}$$

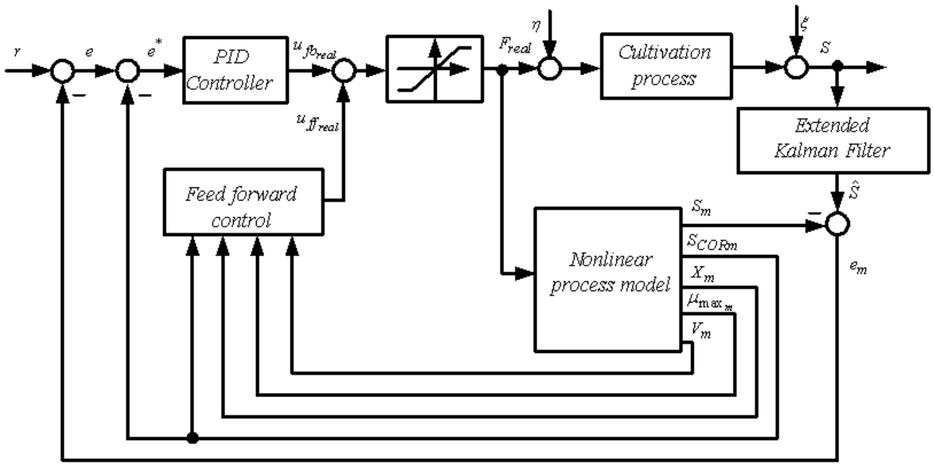

Figure 1. Structure of the control system

where: X_m is the evaluated by model concentration of biomass, $[g \cdot l^{-1}]$; S_m is delayed concentration of substrate (glucose) evaluated by model, $[g \cdot l^{-1}]$; F is feed rate, $[l \cdot h^{-1}]$; S_{in} is substrate concentration of the feeding solution, $[g \cdot l^{-1}]$; V_m is evaluated by model bioreactor volume, [l]; $\mu_{\max_m}$ is model maximum growth rate, $[h^{-1}]$; k_S is saturation constant, $[g \cdot l^{-1}]$; $Y_{S/X}$ is yield coefficient, [-]; S_{CORm} is non-delayed concentration of substrate predicted by model, $[g \cdot l^{-1}]$; η_{γ_X} is biomass concentration process noise, $[g \cdot l^{-1}]$; η_{γ_S} is substrate concentration process noise, $[g \cdot l^{-1}]$; $\eta_{\mu_{\max}}$ is the maximum growth rate process noise, $[h^{-1}]$; $\xi(t)$ is measurement noise, $[g \cdot l^{-1}]$. Here $\mu_{\max_m} = 0.5\ h^{-1}$.

The PID controller algorithm is described as follows:

$$\begin{aligned} u_{fb}(s) &= K_p\left(be(s) - S_{CORm}(s)\right) + \\ &+ \frac{K_p}{T_i} e^*(s) + \frac{T_d s}{1 + \frac{T_d s}{N}}\left(ce(s) - S_{CORm}(s)\right), \end{aligned} \tag{6}$$

where: $u_{fb}(s)$ is the feedback term of control variable, $[l \cdot h^{-1}]$; $r(s)$ is a reference signal, $[g \cdot l^{-1}]$; K_p is proportional gain, [-]; T_i is integral time, [h] T_d is derivative time, [h]; b, c are set-point weight coefficients, [-]; T_d/N is low-pass first order filter of D-term time-constant, [h].

For the E. coli MC4110 cultivation considered here, the process desired set-point (reference signal) is set at $S_{SP} = 0.1\ g \cdot l^{-1}$ glucose concentration [28].

Considering real applications, usually a digital PID controller is implemented. Here, for discretization of the PID controller (Eq. (6)), the backward Euler method [10] is used. The mathematical description of the designed digital PID controller is:

$$u_{fb}(k) = u_p(k) + u_i(k) + u_d(k), \tag{7}$$

$$u_p(k) = K_p\left(be(k) - S_{CORm}(k)\right), \tag{8}$$

$$\begin{aligned} u_i(k) &= u_i(k-1) + b_{i1}\left(e(k) - S_{CORm}(k)\right) + \\ &+ b_{i2}\left(e(k-1) - S_{CORm}(k-1)\right), \end{aligned} \tag{9}$$

$$\begin{aligned} u_d(k) &= a_d u_d(k-1) + \\ &+ b_d\left(ce(k) - ce(k-1) - S_{CORm}(k) + S_{CORm}(k-1)\right), \end{aligned} \tag{10}$$

where

$$b_{i1} = K_p \frac{T_0}{T_i},\ b_{i2} = 0,\ a_d = \frac{T_d}{T_d + NT_0},\ b_d = K_p \frac{T_d N}{T_d + NT_0}.$$

The control variable used to control the feed rate is:

$$F(k) = u_{fb}(k) + u_{ff}(k), \tag{11}$$

where

$$u_{ff}(k) = \frac{1}{Y_{S/X}} \frac{V_m(k)\mu_m(k)X_m(k)}{S_{in} - S_{CORm}} \tag{12}$$

is a feedforward term obtained from the steady state conditions.

Finally, the real control variable has the following form:

$$F_{real}(k) = u_{fb_{real}}(k) + u_{ff}(k), \tag{13}$$

where

$$u_{fb_{real}}(k) = u_{p_{real}}(k) + u_{i_{real}}(k) + u_{d_{real}}(k). \tag{14}$$

The variables $u_{p_{real}}(k)$, $u_{i_{real}}(k)$ and $u_{d_{real}}(k)$ are formed using Eqs. (8) – (10). The error is $e(s) = r(s) - e_m(s)$ [14].

To provide control action designed for specific process requirements, tuning of the PID controller parameters is required. The controller parameters are K_p, T_i, T_d, b, c, T_d/N.

III. Firefly Algorithm

The Firefly Algorithm is a new meta-heuristic algorithm which is inspired from flashing light behaviour of fireflies in nature. The pattern of flashes is often unique for a particular species of fireflies. The two basic functions of such flashes are to attract mating partners or communicate with them, and to attract potential victim. Additionally, flashing may also serve as a protective warning mechanism.

Based on the three idealized rules [18-21], the basic steps of the FA can be summarized as the pseudo code (Fig. 2).

In this algorithm, each firefly has a location x = (x1, ..., xd)T in a d-dimensional space and light intensity I(x) or attractiveness β(x), which are proportional to an objective function f(x). Attractiveness β(x) and light intensity I(x) are relative and these should be judged by the rest fireflies. Thus, attractiveness will vary with the distance ri,j between firefly i and firefly j. So, attractiveness β of a firefly can be defined by Eq. (15) [18-21]:

$$\beta(r) = \beta_0 e^{-\gamma r^m},\ m \geq 1, \tag{15}$$

where r or $r_{i,j}$ is the distance between the i-th and j-th of two fireflies. β_0 is the initial attractiveness at r = 0 and γ is a fixed light absorption coefficient that controls the decrease of the light intensity. In the herewith applied FA, m = 2.

```
begin
Define
 light absorption coefficient γ
 initial attractiveness β0
 randomization parameter α
 objective function f(x), where
 x = (x1, ..., xd)T
Generate initial population of fireflies
xi (i = 1, 2, ..., n)
Determine light intensity Ii at xi via f(xi)
  while (t < MaxGeneration) do
    for i = 1 : n all n fireflies do
      for j = 1 : i all n fireflies do
        if (Ij > Ii) then
        Move firefly i towards j
        based on Eq. (7)
        end if
        Attractiveness varies with
        distance r via exp[-γr2]
        Evaluate new solutions and
        update light intensity
      end for j
    end for i
    Rank the fireflies and find
    the current best
  end while
  Postprocess results and visualization
end begin
```

Figure 2. Pseudo code of FA

The initial solution is generated based on:

$$x_j = \mathrm{rand}(Ub - Lb) + Lb, \tag{16}$$

where rand is a random number generator uniformly distributed in the space [0, 1]; Ub and Lb are the upper range and lower range of the j-th firefly, respectively.

When firefly i is attracted to another more attractive firefly j, its movement is determined by:

$$x_{i+1} = x_i + \beta_0 e^{-\gamma r_{i,j}^2}(x_i - x_j) + \alpha(\mathrm{rand} - \frac{1}{2}), \tag{17}$$

where the first term is the current position of a firefly, the second term is used for considering a firefly's attractiveness to light intensity seen by adjacent fireflies $\beta(r)$ (Eq. (15)), and the third term is used to describe the random movement of a firefly in case there are no brighter ones. The coefficient α is a randomization parameter determined by the problem of interest. The distance $r_{i,j}$ between any two fireflies i and j at $\mathbf{x}_i$ and $\mathbf{x}_j$, respectively, is defined as a Cartesian or Euclidean distance, according to [18-21]:

$$r_{i,j} = \left\| x_i - x_j \right\| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2}, \tag{18}$$

where $x_{i,k}$ is the k-th component of the spatial coordinate $\mathbf{x}_i$ of the i-th firefly.

IV. Results and Discussion

A series of tuning procedures for the considered control system using FA are performed. Computer specifications to run all optimization procedures are Intel® Core™i5-2320 CPU @ 3.00GHz, 8 GB Memory (RAM), Windows 7 (64bit) operating system.

The parameters of the FA are tuned based on several pre-tests according to the problem considered here. After tuning procedures, the main FA parameters are set to the optimal settings: $\beta_0 = 1$, $\gamma = 1$, $\alpha = 0.2$, number of fireflies = 25, number of iterations = 50.

Because of the stochastic characteristics of the applied algorithms, a series of 30 runs for each algorithm are performed and the best results are presented.

To evaluate the significance of the tuning procedure and controller performance the integrated square error (I_{ISE}) criterion is used:

$$I_{ISE} = \int_0^T e\ t\ ^2 dt, \tag{19}$$

where t is time, h; T is end time of the cultivation, h.

A. Case I: Tuning of controller parameters K_p, T_i and T_d

In this case the tuning of the three controller parameters is considered. The coefficients b, c and N are set to the following values [14]: b = 1, c = 1 and N = 30. The range of the tuning parameters is considered, as follows: $Kp \in [0, 2]$, $Ti \in [0, 2]$, $Td \in [0, 0.1]$.

For comparison of FA and GA, a series of tuning procedures for the considered control system using GA are performed, too. For realistic comparison, the GA is run for the same number of function evaluations, namely 1250. The GA parameters are: the number of generations is set at 50; the number of individuals is set at 25; a roulette wheel mechanism is employed; double point crossover with crossover probability of 0.7 is accepted; mutation with low probability in the range 0.01 is randomly applied; a generation gap of 0.97 is chosen, and fitness-based reinsertion is used.

As a result of the FA and GA tuning, the optimal PID controllers settings are obtained. The numerical values of the controllers parameters, objective functions values, total computational times and number of functions evaluations are presented in Table I. In this case, it is observed that FA shows identical performance to GA performance with respect to computational time and obtained objective function values. The two meta-heuristics solve the tuning problem with the same quality – $I_{ISE} = 16.86$.

TABLE I

CASE I: RESULTS FROM PID CONTROLLER TUNING

Parameter	Obtained best values	
	FA	GA
K_p	0.4927	0.5450
T_i	0.4629	0.5917
T_d	0.0030	0.0031
I_{ISE}	**16.8625**	**16.8653**
total time, s	165.5401	170.0924
N_{FE}	1250	1250

In the next figures, some graphical results of the control system performance for E. coli fed-batch cultivation process are presented. As it can be seen from Fig. 3, up to 15 h controllers show identical performance – the resulting errors between control variable and reference signal (I_{ISE}) are identical. After 15 h, both controllers fail to keep the substrate concentration to set point of 0.1 $g \cdot l^{-1}$. However, GA tuned PID controller accumulates bigger error in the end of the process compared to the FA tuned PID controller (Fig. 3, solid line). Resulting profiles of the control variable are shown on Fig. 4.

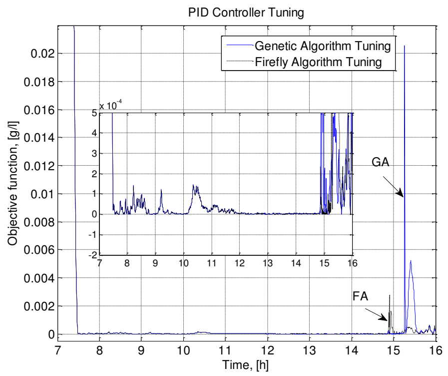

Figure 3. I_{ISE} during the time (Case I)

Although the observed objective function values of the two meta-heuristics are very close, the FA tuned PID controller shows better performance than the GA tuned one. Further, FA is compared to the GA for a more complex case – six PID controller parameters tuning.

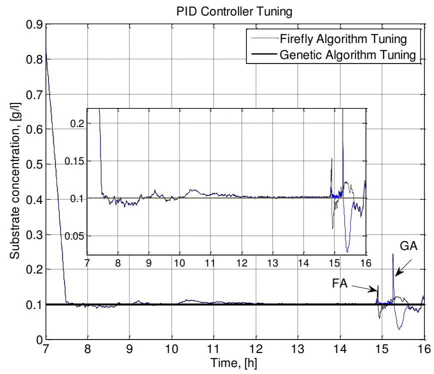

Figure 4. Control variable - glucose concentration (Case I)

In Fig. 5, the resulting control signal (feed rate profile) is shown.

B. Case II: Tuning of controller parameters K_p, T_i, T_d, b, c and N

The range of the tuning parameters is considered as follows: $K_p \in [0, 2]$, $T_i \in [0, 2]$, $T_d \in [0, 0.1]$, b, c $\in [0, 5]$, N $\in [0, 50]$. The obtained numerical values of the FA and GA controllers' parameters, objective functions values, total computational times and number of functions evaluations are presented in Table II.

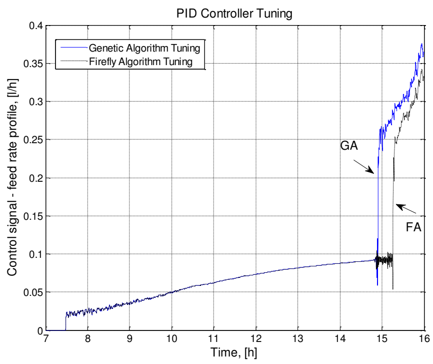

Figure 5. Control signal – feed rate profiles (Case I)

TABLE II

CASE II: RESULTS FROM PID CONTROLLER TUNING

Parameter	**Obtained best values**	
	FA	**GA**
K_p	0.3031	0.5227
T_i	0.4912	0.1983
T_d	0.0034	0.0061
b	0.0986	1.0365
c	1.6207	0.9764
N	19.9520	1.2357
I_{ISE}	**16.8410**	**16.8706**
total time, s	178.7211	185.8908
N_{FE}	1250	1250

In this case, the FA tuned PID controller has superior performance compared to the GA tuned controller. For the same number of function evaluations, the FA reached better values for I_{ISE} compared to GA. In Fig. 6 and Fig. 7, the control variable (substrate concentration) and observed objective function are presented.

As a result of FA tuning procedure, a set of optimal PID controller parameters is obtained. Thus, for a short time, the controller sets the control variable and maintains it at the desired set point (0.1 g·l^{-1}) to the end of fed-batch cultivation process. GA tuned PID controller fails in the last 1 hour of the cultivation. The results imply that the FA is potentially more powerful in solving optimization problem considered here.

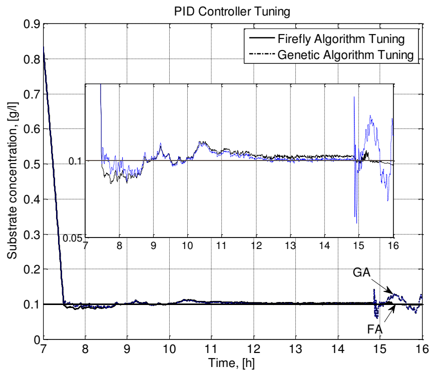

Figure 6. Control variable - glucose concentration (Case II)

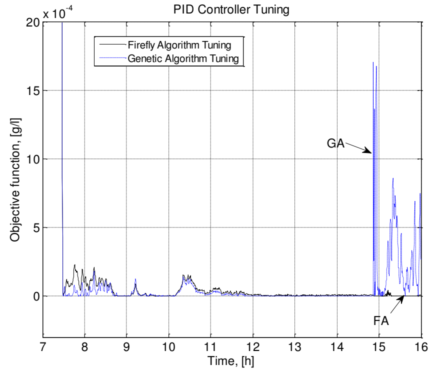

Figure 7. I_{ISE} during the time (Case II)

The resulting control signal is shown in Fig. 8.

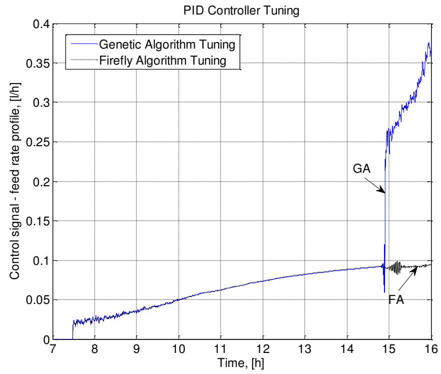

Figure 8. Control signal – feed rate profiles (Case II)

V. CONCLUSIONS

The paper presents optimal tuning of PID controller, using the recently developed FA. 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. The mathematical model of the cultivation process is represented by the dynamic mass balance equations for main process variables – biomass and substrate concentration.

A series of tuning procedures for PID controllers tuning, using FA, are performed. The FA parameters are problem-oriented and specifically chosen to achieve an adequate and accurate decision. It is demonstrated that the FA provides simple, efficient and accurate approach of tuning the Smith Predictor structure based on PID controller. As a result, a set of optimal PID controller parameters is obtained. For a short time, the controllers set the control variable and maintain it at the desired set-point during the cultivation process. Thus, a good closed-loop system performance is achieved.

In order to compare the obtained results with another meta-heuristic algorithm, a series of tuning procedures using GA are performed, too. Based on the comparison, it could be concluded that FA, shows superior performance for PID controller parameter tuning of the considered nonlinear control system.

Finally, it is shown that the PID controller tuning using FA can be considered as an effective approach for the achievement of high quality and better performance of the designed control system for cultivation processes.

ACKNOWLEDGMENT

This work has been partially supported by the Bulgarian National Science Fund under the Grants DID 02/29 “Modelling Processes with Fixed Development Rules (ModProFix)” and DMU 02/4 “High quality control of biotechnological processes with application of modified conventional and metaheuristics methods”.

REFERENCES

[1] K. Aström and T. Hagglund, Advanced PID Control, Instrument Society of America, 2006.

[2] E. Garipov, PID Controllers, Automatics and Informatics, Vol. 3, 2006 (in Bulgarian).

[3] O. Gundogdu, "Optimal-tuning of PID Controller Gains using Genetic Algorithms", Journal of Engineering Sciences, Vol. 11, No. 1, 2005, pp. 131-135.

[4] J. S. Kim, J.-H. Kim, J.-M. Park, S.-M. Park, W.-Y. Choe and H. Heo, "Auto Tuning PID Controller based on Improved Genetic Algorithm for Reverse Osmosis Plant", World Academy of Science, Engineering and Technology, Vol. 47, 2008, pp. 384-389.

[5] S. M. G. Kumar, B. Rakesh and N. Anantharaman, "Design of Controller using Simulated Annealing for a Real Time Process", International Journal of Computer Applications, Vol. 2, 2010, pp. 1053-1368.

[6] E. Bonabeau, M. Dorigo and G. Theraulaz, Swarm Intelligence: From Natural to Artificial Systems, New York,Oxford University Press, 1999.

[7] J. Brownlee, Clever Algorithms. Nature-Inspired Programming Recipes. LuLu, p. 436, 2011.

[8] W. P. Syam and I. M. Al-Harkan, "Comparison of Three Meta Heuristics to Optimize Hybrid Flow Shop Scheduling Problem with Parallel Machines", World Academy of Science, Engineering and Technology, Vol. 62, 2010, pp. 271-278.

[9] N. Tahouni, R. Smith and M. H. Panjeshahi, "Comparison of Stochastic Methods with Respect to Performance and Reliability of Low-temperature Gas Separation Processes", The Canadian Journal of Chemical Engineering, Vol. 88, No. 2, 2010, pp. 256-267.

[10] M. J. Dashti, S. G. Kambiz, S. M. H. Seyedkashi and T. M. Behnam, "Novel Simulated Annealing Algorithm in Order to Optimal Adjustment of Digital PID Controller", In: 11th Int. Conf. on Control Automation Robotics & Vision (ICARCV), 7-10 Dec. 2010, pp. 1766-1771.

[11] A. H. Y. Yacoub, S. Buyamin and N. A. Wahab, "Integral Time Absolute Error Minimization for PI Controller on Coupled-tank Liquid Level Control System based on Stochastic Search Techniques", Journal Technology, Vol. 54, 2011, pp. 381-402.

[12] K. Ganapathy and J. Jovitha, "Control of Dead Time Systems Using Improved Tabu Search", Int. J. of Soft Computing, Vol. 5, No. 4, 2010, pp. 177-184.

[13] A. Oonsivilai and P.-L.-O. Padej, "Optimum PID controller tuning for AVR system using adaptive tabu search", In: 12th WSEAS International Conference on Computers, 2008, pp. 987-992.

[14] D. Puangdownreong, T. Kulworawanichpong and S. Sujitjorn, "Input weighting optimization for PID controllers based on the adaptive tabu search", In: IEEE TENCON, Vol. 4, 2004, pp. 451-454.

[15] Q. Wang, P. Spronck and R. Tracht, "An Overview of Genetic Algorithms Applied to Control Engineering Problems", Machine Learning and Cybernetics, Vol. 3, 2003, pp. 1651-1656.

[16] R. A. Krohling and J. P. Rey, "Design of Optimal Disturbance Rejection PID Controllers Using Genetic Algorithm", IEEE Trans. Evol. Comput., Vol. 5, 2001, pp. 78-82.

[17] Ts. Slavov and O. Roeva, "Genetic Algorithm Tuning of PID Controller in Smith Predictor for Glucose Concentration Control", Int. J. Bioautomation, Vol. 15, No. 2, 2011, pp. 101-114.

[18] X. S. Yang, Nature-inspired Meta-heuristic Algorithms, Luniver Press, Beckington, UK, 2008.

[19] X. S. Yang, "Firefly Algorithm for Multimodal Optimization, Lecture Notes in Computing Sciences", Vol. 5792, 2009, pp. 169-178.

[20] X. S. Yang, "Firefly Algorithm, Levy Flights and Global Optimization", Research and Development in Intelligent Systems XXVI, Springer, London, UK, 2010a, pp. 209-218.

[21] X. S. Yang, Firefly Algorithm, "Stochastic Test Functions and Design Optimisation", International Journal of Bio-inspired Computation, Vol. 2, No. 2, 2010b, pp. 78-84.

[22] B. Nasiri and M. R. Meybodi, "Speciation-based Firefly Algorithm for Optimization in Dynamic Environments", Int. J. Artificial Intelligence, Vol. 8(S12), 2012, pp. 118-132.

[23] T. Apostolopoulos and A. Vlachos, "Application of the Firefly Algorithm for Solving the Economic Emissions Load Dispatch Problem", International Journal of Combinatorics, Article ID 523806, 2011.

[24] A. Yousif, A. H. Abdullah, S. M. Nor and A. A. Abdelaziz, "Scheduling Jobs on Grid Computing using Firefly Algorithm", Journal of Theoretical and Applied Information Technology, Vol. 33(2), 2011, 155-164.

[25] N. Chai-ead, P. Aungkulanon and P. Luangpaiboon, "Bees and Firefly Algorithms for Noisy Non-linear Optimisation Problems", Prof. Int.

Multiconference of Engineers and Computer Scientists, Vol. 2, 2011, pp. 1449-1454.

[26] O. J. M. Smith, "A Controller to Overcome Dead Time", ISA Journal, Vol. 6, 1959, pp. 28-33.

[27] M. Galvez-Carrillo, R. De Keyser and C. Ionescu, "Application of a Smith Predictor based Nonlinear Predictive Controller to a Solar Power Plant", Preprints of the 7th IFAC Symposium on Nonlinear Control Systems, 21-24 August, Pretoria, South Africa, 2007, pp. 188-193.

[28] M. Arndt and B. Hitzmann, "Feed Forward/feedback Control of Glucose Concentration during Cultivation of Escherichia coli", Proc. 8th IFAC Int. Conf. on Comp. Appl. in Biotechn, 2001, pp. 425-429.