Al-Khwarizmi Engineering Journal

Al-Khwarizmi Engineering Journal, Vol. 9, No. 4, P.P. 46- 53 (2013)

Design of an Adaptive PID Neural Controller for Continuous Stirred Tank Reactor based on Particle Swarm Optimization

Khulood A. Dagher* **Ahmed S. Al-Araji****

** Department of Computer Science / College of Science / University of Baghdad*

*** Department of Control and Systems Engineering / University of Technology*

*Email:dagherkhulood@yahoo.com

*Email:Ahmedsas2040@yahoo.com

(Received 16 May 2013; accepted 11 November 2013)

Abstract

A particle swarm optimization algorithm and neural network like self-tuning PID controller for CSTR system is presented. The scheme of the discrete-time PID control structure is based on neural network and tuned the parameters of the PID controller by using a particle swarm optimization PSO technique as a simple and fast training algorithm. The proposed method has advantage that it is not necessary to use a combined structure of identification and decision because it used PSO. Simulation results show the effectiveness of the proposed adaptive PID neural control algorithm in terms of minimum tracking error and smoothness control signal obtained for non-linear dynamical CSTR system.

Keywords: *Particle Swarm Optimization, PID Controller, Neural Network, CSTR.*

1. Introduction

In recent years, the adaptive control techniques in the industry process have made great advances. Numerous control methods such as adaptive neural control and adaptive fuzzy control have been studied. Among them, the best known is the adaptive proportional-integral-derivative (PID) controller, which has been widely used in the industry because of its simple structure and robust performance in a wide range of operating conditions [1]. There are many classic tuning methods for PID parameters such as trial and error method or Ziegler-Nichol's method.

Unfortunately, it has been quite difficult to tune properly the gains of PID controllers because many industrial plants are often burdened with problems such as high order, time delays, and nonlinearities. It is hard to determine optimal or near optimal PID parameters with the classic tuning method. For these reasons, it is highly desirable to increase the capabilities of PID controllers by adding new features. Many artificial intelligence (AI) techniques have been employed to improve the controller performances for a wide range of plants while retaining their basic characteristics [2].

In addition to that, there are many control methodologies for continuous stirred tank reactor (CSTR) system that it's strong nonlinear behavior such as follows.

A PID self adaptive control method based on on-line optimization of PID controller parameters by the differential evolution algorithm is stated in [3].

A practical non-linear PID controller that utilizes a local model (LM) network, which combines a set of local models within an artificial neural network (ANN) structure, to adaptively characterize the CSTR process nonlinearity is explained in [2].

The control of CSTR using state feedback gain using pole placement technique is investigated in [4]. The state feedback gain parameters are gain scheduled using Fuzzy Logic Control to provide the appropriate values for the different regions.

In [5] it is used two strategies for adaptive control of a nonlinear CSTR process, adaptive general predict control and model reference adaptive control the polynomial approach connected with pole-placement method. The Artificial Neuro-Fuzzy Inference System (ANFIS) gain scheduled Genetic Algorithm (GA) based PID is proposed for CSTR as in [6].

Also in [7] is proposed a predictive control strategy for nonlinear dynamics of a CSTR process based on a neuro-fuzzy network and L infinite. Hybrid adaptive inverse control based on neural fuzzy system is presented and explained in [8]. It consists of two control loops, inverse control and PID control. PID control is a complement for inverse control and is mainly used to eliminate static error existing in direct inverse control when the inverse model is uncertain.

A nonlinear model predictive control (NMPC) based on Wiener model and Laguerre function is proposed in [9]. Employing a Wiener model in NMPC can handle the nonlinearity in the controlled CSTR plant and retain all important properties of linear model predictive control (MPC) with a quadratic function.

The main advantage of the presented approach is not necessary to use a combined structure of identification and decision, common in a standard self-tuning controller because it is used a particle swarm optimization (PSO) as a simple steps algorithm and fast tuning the parameters of the PID controller.

The remainder of this paper is organized as follows: section two is a description of the mathematical model of the CSTR. In section three, the proposed of neural network like self-tuning PID controller approach and tuning algorithm are derived. Simulation results of the proposed adaptive PID neural control algorithm are presented in section four and the conclusions are drawn in section five.

2. CSTR Mathematical Modeling

Consider standard two-state (CSTR) with an exothermic irreversible first-order reaction $A \rightarrow B$ take place, the heat of reaction is removed by a coolant medium that flows through a jacket around the reactor as shown in Figure (1) [10 and 11]. The dynamics of system can be described by the following two nonlinear ordinary differential equations [10, 11, 12 and 13]:

$$\frac{\partial C_a(t)}{\partial t} = \frac{q}{Vol}(C_{af} - C_a(t)) - K_o \times C_a(t) \times e^{\left(\frac{-E}{RT(t)}\right)} \quad \ldots(1)$$

$$\frac{\partial T(t)}{\partial t} = \frac{q}{Vol}(T_f - T(t)) + \frac{(-\Delta H) \times K_o \times C_a(t)}{\rho \times C_\rho} \times e^{\left(\frac{-E}{RT(t)}\right)}$$

$$+ \frac{\rho_c \times C_{\rho c}}{\rho_c \times C_{\rho c} \times Vol} \times q_c(t) \left(1 - e^{\left(\frac{-h_a}{q_c(t) \times \rho_c \times C_{\rho c}}\right)} \right) \times (T_{cf} - T(t))$$

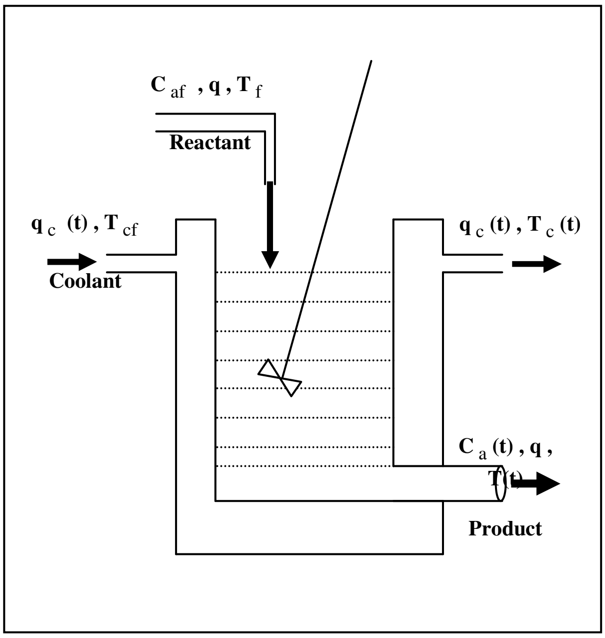

Fig .1. CSTR with Cooling Jacket.

The nominal CSTR operating conditions can be shown in Table (1).

Table ,
Nominal CSTR Operating Conditions.

Parameter	Description	Nominal Value
q	Process flow-rate	100 $lmin^{-1}$
$\mathbf{C_{af}}$	Intel feed concentration	1 mol l^{-1}
$\mathbf{T_f}$	Feed temperature	350K
$\mathbf{T_{cf}}$	Inlet coolant temperature	350K
Vol	Reactor volume	100 l
$\mathbf{h_a}$	Heat transfer coefficient	$7*10^{10}$ cal $min^{-1}.K^{-1}$
$\mathbf{k_o}$	Reaction rate constant	$7.2*10^{10}$ Min^{-1}
E/R	Activation energy	$9.95*10^3$ K
ΔH	Heat of reaction	$2*10^5$ cal mol^{-1}
ρ, ρ_c	Liquid densities	1000 g l^{-1}
$\mathbf{C_p}$ $\mathbf{C_{pc}}$	Specific heats	1 cal g^{-1}. K^{-1}
$\mathbf{q_c}$	Coolant flow-rate	103.41 $l.min^{-1}$
T	Reactor temperature	440.2K
$\mathbf{C_a}$	Product concentration	$8.36*10^{-2}$ mol l^{-1}

3. PID Neural Controller Approach

The approach used to control the nonlinear system depends on the information available about the system and the control objectives; therefore, the general structure of the PID neural controller is shown in Figure (2).

The feedback PID neural controller is very important because it is necessary to stabilize the tracking error of the system when the output of the system is drifted from the reference point.

The self-tuning PID neural controller is shown in figure (3). It is based on a conventional PID controller, which consists of three terms: proportional, integral and derivative. The standard form of a PID controller is given in the s-domain as in equation (2) [15].

$$Gc(s) = P + I + D = K_p + \frac{K_i}{s} + K_d s \qquad \ldots(2)$$

where K_p, K_i and K_d are called the proportional gain, the integral gain and the derivative gain respectively.

The aim of adaptive self-tuning technique is to adjust the parameters of the PID neural controller by using particle swarm optimization algorithm technique.

The proposed self-tuning PID neural control scheme is like neural network PID controller structure as the discrete-time equation (3) [16].

$$u(k) = u(k-1) + Kp[e(k) - e(k-1)] + Kie(k) + Kd[e(k) - 2e(k-1) + e(k-2)] \qquad \ldots.(3)$$

Therefore, the self-tuning PID input vector consists of e(k), e(k-1), e(k-2) and u(k-1), where e(k) and u(k-1) denote the input error signals and the self-tuning PID output respectively.

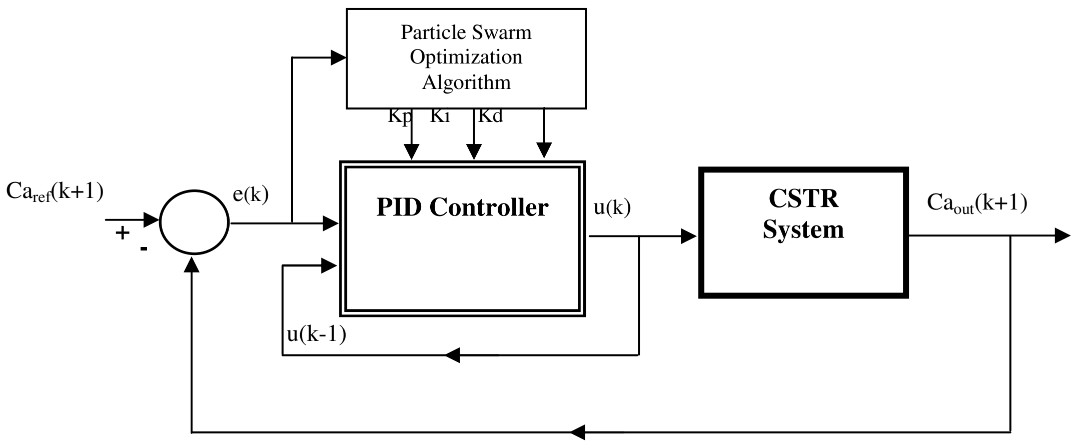

Fig. 2. The Proposed Block Diagram of Neural Network Like Self Tuning PID Controller.

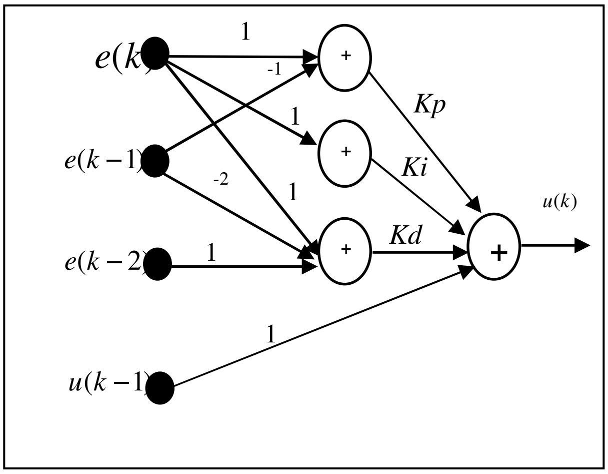

Fig. 3. The Neural Network Like Self Tuning PID Controller Architecture.

3.1. Learning Algorithm

Particle Swarm optimization is a kind of algorithm to search for the best solution by simulating the movement and flocking of birds. PSO algorithms use a population of individual (called particles) "flies" over the solution space to search for the optimal solution.

Each particle has its own position and velocity to move around the search space. The particles are evaluated using a fitness function to see how close they are to the optimal solution [17, 18 and 19].

The previous best value is called as pbest. Thus, pbest is related only to a particular particle. It also has another value called gbest, which is the best value of all the particles pbest in the swarm.

The neural network like self-tuning PID controller with three weights parameters of the PID controller matrix is rewritten as an array to form a particle. Particles are then initialized randomly and updated afterwards according to equations (4, 5, 6, 7, 8 and 9) [17, 18 and 19] in order to tune the PID parameters:

$$\Delta Kp_m^{k+1} = \Delta Kp_m^k + c_1 r_1 (pbest_m^k - Kp_m^k) + c_2 r_2 (gbest^k - Kp_m^k) \quad \ldots(4)$$

$$Kp_m^{k+1} = Kp_m^k + \Delta Kp_m^{k+1} \quad \ldots(5)$$

$$\Delta Ki_m^{k+1} = \Delta Ki_m^k + c_1 r_1 (pbest_m^k - Ki_m^k) + c_2 r_2 (gbest^k - Ki_m^k) \quad \ldots(6)$$

$$Ki_m^{k+1} = Ki_m^k + \Delta Ki_m^{k+1} \quad \ldots(7)$$

$$\Delta Kd_m^{k+1} = \Delta Kd_m^k + c_1 r_1 (pbest_m^k - Kd_m^k) + c_2 r_2 (gbest^k - Kd_m^k) \quad \ldots(8)$$

$$Kd_m^{k+1} = Kd_m^k + \Delta Kd_m^{k+1} \quad \ldots(9)$$

$m = 1,2,3,.....pop$

where

pop is number of particles.

$Kpid_m^k$ is the weight of particle *m* at *k* iteration.

c_1 and c_2 are the acceleration constants with positive values equal to 2.

r_1 and r_2 are random numbers between 0 and 1.

$pbest_m$ is best previous weight of m^{th} particle.

$gbest$ is best particle among all the particle in the population.

The number of dimension in particle swarm optimization is equal to three because there are only three parameters of the PID controller.

The mean square error function is chosen as criterion for estimating the model performance as equation (10):

$$E = \frac{1}{2}\sum_{j=1}^{pop}(Ca_{ref}(k+1)^j - Ca_{out}(k+1)^j)^2 \quad \ldots(10)$$

The steps of PSO for neural network like self-tuning PID controller can be described as follows:

- **Step1** Initial searching points $Kp_1^0, Ki_1^0, Kd_1^0, \Delta Kp_1^0, \Delta Ki_1^0$ and ΔKd_1^0 of each particle are usually generated randomly within the allowable range. Note that the dimension of search space is consists of all the parameters used in the neural network like PID controller as shown in Figure (3). The current searching point is set to *pbest* for each particle. The best-evaluated value of *pbest* is set to *gbest* and the particle number with the best value is stored.
- **Step2** The objective function value is calculated for each particle by using equation (10). If the value is better than the current pbest of the particle, the pbest value is replaced by the current value. If the best value of pbest is better than the current gbest, gbest is replaced by the best value and the particle number with the best value is stored.
- **Step3** The current searching point of each particle is update by using equations (4, 5, 6, 7, 8 and 9).
- **Step4** If the current iteration number reaches the predetermined maximum iteration number, then exit. Otherwise, go to step 2.

4. Simulation Results

The dynamic model of the CSTR described in section 2 is used where the objective is to control the Ca(t), which can be done by introducing a coolant flow rate qc(t) as the manipulated variable, also the temperature can be varied too. To study the dynamic behavior of the CSTR model, the open loop output response of the CSTR for step changes in the coolant flow-rate is shown in figures (4-a & b) respectively by using the fourth order RK method [20] with sampling time of 0.1 minute through the Matlab/Simulink computer simulation.

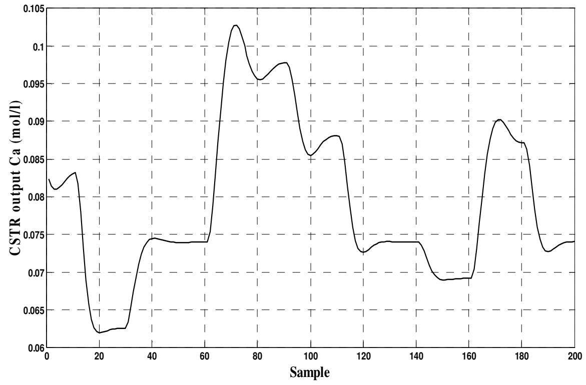

Fig. 4-a. The Open Loop Respose of the CSTR.

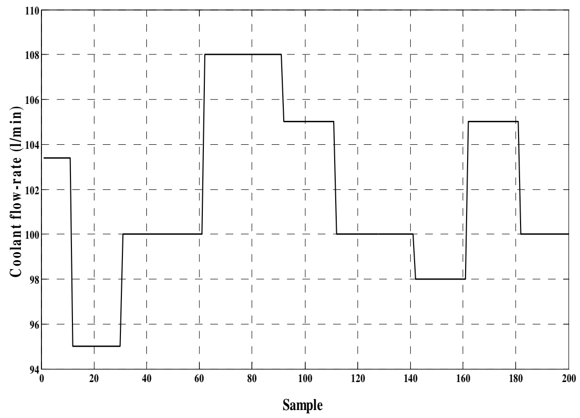

Fig. 4-b. The Step Changes in the Coolant Flow-Rate.

As shown in Figure (4), both the damping and the steady-state gain of the system varies considerably, depending on the set point, which gives an indication of the highly nonlinear dynamic behavior of the system.

The proposed neural network like self-tuning PID controller scheme as in Figure (2) is applied to the CSTR model and it is used the proposed learning algorithm steps of PSO for tuning PID controller's parameters. The PSO algorithm is set to the following parameters:

Population of particle is equal to 20 and number of iteration is equal to 300.Number of in each particle is 3 because there are three parameters of PID.

It is very necessary to normalize the input signals of Figure (4-a) and the coolant flow-rate as the manipulated variable of Figure (4-b) between (-1 to +1). The signals entering to or emitted from the network have been normalized to lie within (-1 to +1) in order to overcome numerical problems that is involved within real values. Scaling functions have to be added at the neural network terminals to convert the scaled values to actual values and vice versa.

After training, it can be observed that the actual output of the CSTR plant is following the desired input that is shown the Figure (5) while the feedback control action is shown in Figure (6) that has small spike in the transit state and fix output at steady-state.

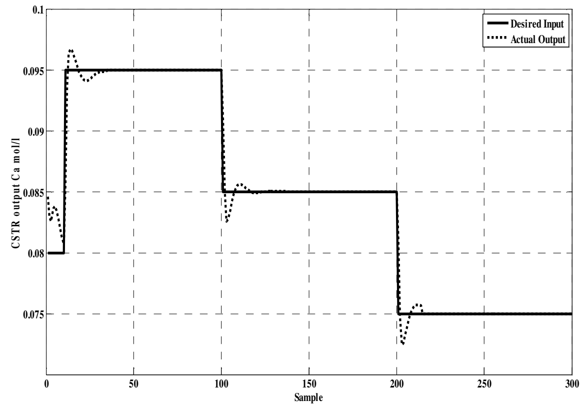

Fig. 5. Response of the CSTR Plant Output & the Desired Input.

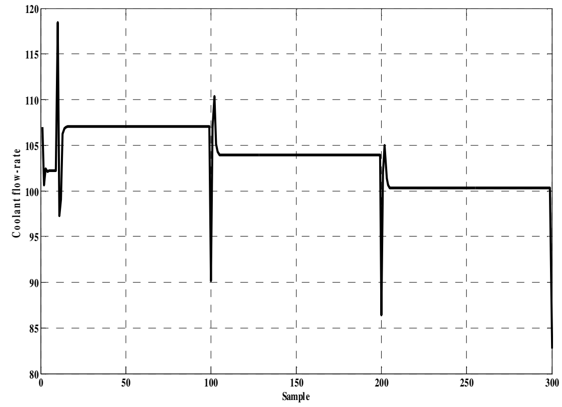

Fig. 6. The Feedback PID Control Signal.

The error between the desired input and the actual output of the plant is very small as shown in Figure (7).

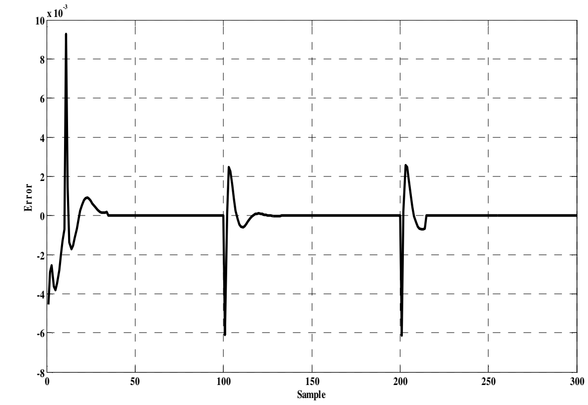

Fig. 7. Output Error between the Set Point Desired & the Actual Output.

The gains of the PID self-tuning neural controller as scale function is shown in Figure (8).

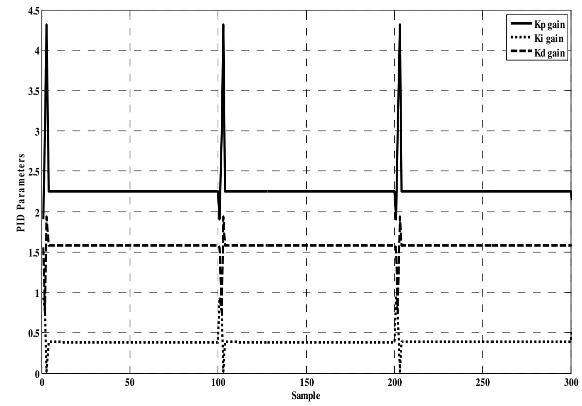

Fig. 8. The PID Controller's Parameters.

5. Conclusion

In this paper, the structure of the neural network –like self tuning PID controller with particle swarm optimization algorithm technique learned as the proposed structure of controller and successfully simulated to nonlinear dynamic CSTR system. Using PID feedback controller with self-tuning technique to adjust the parameters (Kp, Ki, Kd) of the controller. So that, the output of the plant follows the desired input and PSO algorithm is used to tune the PID controller with minimum time and more stability of the controller and no oscillation with best parameters of the controller. The proposed control structure has shown the ability to minimize the tracking error in the transient state less than 0.01 between the desired input and the actual output of the CSTR plant and in the steady state, the tracking error is equal to zero, as well as to reduce the spike control action with a simple and fast training algorithm.

Acknowledgment

The authors would like to express their appreciation to Automation and Robotics Research Unit (ARRU) at Control and Systems Engineering Dept. in the University of Technology for providing them the requirements of this research.

6. References

[1] T. Wonghong and S. Engell, Real-time PI Controller Tuning via Unfalsified Control, The Proceedings of IEEE International Symposium on Intelligent Control (ISIC), Part of 2011 IEEE Multi-Conference on Systems and Control Denver, CO, USA. September 28-30, 2011, pp. 1008-1013.

[2] R. Gao, A. Odywer and E. Coyle, A Non-linear PID Controller for CSTR Using Local Model Networks, Proceedings of the 4th World Congress on Intelligent Control and Automation June 10-14, 2002, Shanghai, P.R.China., pp. 3278-3282.

[3] X. Zhicheng, The Application in Adaptive Control for Differential Evolution Algorithm, Proceedings of the International Conference on System Science, Engineering Design and Manufacturing Information, 2011, pp. 206-209.

[4] U. Sabura and G. Uma, Fuzzy Gain Scheduled Pole Placement Based State Feedback Control of CSTR, IET-UK International Conference on Information and Communication Technology in Electrical Sciences (ICTES 2007), Dr. M.G.R. University, Chennai, Tamil Nadu, India. Dec. 20-22, 2007. pp.63-68.

[5] M. Delbari, K. Salahshoor and B. Moshiri, Adaptive Generalized Predictive Control and Model Reference Adaptive Control for CSTR Reactor, International Conference on Intelligent Control and Information Processing August 13-15, 2010 - Dalian, China, pp. 165-169.

[6] U. Sabura and G. Uma, ANFIS Gain Scheduled CSTR with Genetic Algorithm

Based PID Minimizing Integral Square Error, IET-UK International Conference on Information and Communication Technology in Electrical Sciences (ICTES 2007), Dr. M.G.R. University, Chennai, Tamil Nadu, India. Dec. 20-22, 2007, pp. 57-62.

[7] Q. Wu, Y.J. Wang, Q.M. Zhu and K. Warwick, Neurofuzzy model based L^{∞} predictive control of nonlinear CSTR system, Proceedings of the 2002 IEEE international Conference on Control Applications September 18-20, 2002, Glasgow, Scotland, U.K. pp. 59-64.

[8] J. Li and Y. Jinshou, Nonlinear Hybrid Adaptive Inverse Control Using Neural Fuzzy System and Its Application To CSTR Systems, Proceedings of the 4th World Congress on Intelligent Control and Automation June 10-14, 2002, Shanghai, P.R.China, pp. 1896-1900.

[9] A. Harudeen and D. Banjerpongchai, Nonlinear Model Predictive Control with Wiener Model and Laguerre Function for CSTR Process. The Proceedings of 8th Electrical Engineering! Electronics, Computer, Telecommunications and Information Technology (ECTI) Association of Thailand - Conference 2011, pp. 577-580.

[10] L.S. Saoud, F. Rahmoune, V. Tourtchine and K. Baddari, An Inexpensive embedded electronic continuous stirred tank reactor (CSTR) based on neural networks, Proceeding of the International Conference on Multimedia Technology (ICMT2011), pp. 6233-6237, 2011.

[11] M. Delbari, K. Salahshoor and B. Moshiri, Adaptive generalized predictive control and model reference adaptive control for CSTR reactor, Proceedings of the International Conference on Intelligent Control and Information, Dalian, China, August 13-15, pp. 165-169, 2010.

[12] P. Guo, nonlinear predictive functional control based on hopfield network and its application in CSTR, Proceedings of the 5th International Conference on Machine Learning and Cybernetics, Dalian, August 13-16, pp. 3036-3039, 2006.

[13] B.C. Juricek, D.E. Seborg and W.E. Larimore, Process control applications of subspace and regression-based identification and monitoring methods, 2005 American Control Conference, Portland, OR, USA, June 8-10, pp. 2341-2346, 2005.

[14] E.P. Nahas, M.A. Henson and D.E. Seborg, Nonlinear internal model control strategy for neural network models, Computers Chem. Eng., Vol. 16, no. 12, pp. 1039-1057, 1992.

[15] Q. Zhong, "Robust Control of Time-delay Systems", Springer – Verlag London Limited 2006

[16] S. Omatu, M. Khalid, and R. Yusof, Neuro-Control and its Applications. London: Springer-Velag, 1995.

[17] J. Derrac, S. Garc, D. Molina and F. Herrera ,A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms, Journal of Swarm and Evolutionary Computation, Vol.1,pp. 3–18, 2011.

[18] J. Zhou, Z. Duan, Y. Li, J. Deng and D. Yu, PSO-based neural network optimization and its utilization in a boring machine, Journal of Materials Processing Technology, Vol.178, pp.19–23, 2006.

[19] Y.S. Lee, S.M. Shamsuddin, and H.N. Hamed, Bounded PSO Vmax Function in Neural Network Learning, Proceedings of the Eighth International Conference on Intelligent Systems Design and Applications, pp.474-479, 2008.

[20] K. Ogata, Modern Control Engineering. 4th Edition, by Addison- Wesley Publishing Company, Inc. 2003.

تصميم مسيطر عصبي (PID) متكيف لخزان مفاعل مستمر الإثارة مبني على أساس أمثلية حشد الجسيمات

خلود اسكندر داغر* **أحمد صباح الاعرجي****

*قسم علوم الحاسبات / كلية العلوم / جامعة بغداد

**قسم هندسة السيطرة والنظم / الجامعة التكنولوجية

*البريد الالكتروني: dagherkhulood@yahoo.com

**البريد الالكتروني: ahmedsas2040@yahoo.com

الخلاصة

أن هذا البحث يقدم خوارزمية أمثلية حشد الجسيمات مع الشبكة العصبية التي تشبه المسيطر (PID) ذات التنغيم التلقائي لمنظومة خزان مفاعل مستمر الإثارة.

أن هيكلية المسيطر (PID) مبني على أساس الشبكة العصبية و تنغيم عناصر المسيطر (PID) تتم من خلال تقنية خوارزمية حشد الجسيمات لأنها بسيطة و سريعة التعلم. أن فائدة هذه الطريقة المقترحة هي لا تحتاج إلى عملية التعريف للمنظومة بسبب استخدام أمثلية حشد الجسيمات.

من خلال نتائج المحاكات نلاحظ فعالية هذه الخوارزمية للمسيطر العصبي (PID) المتكيف من حيث اقل خطأ تتابعي و الحصول على أشارة سيطرة ناعمة لمنظومة ديناميكية لاخطية التصرف.