Karkar Nora[1], Zerroug Nadjat[2], Tighilt Yamina[3], Benmhammed Khier[4]

[1,4]LSI Laboratory,[2]Quere Laboratory, [3]LIS Laborator,Faculty of engineering , Department of Electronic, University Ferhat Abbas of Setif

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Control of PID parameters by iterative learning based on neural network

Abstract *Iterative learning refers to the development, analysis and implementation of methods that allow a machine to evolve through a learning process, and thus perform tasks that are difficult or impossible to perform by more conventional algorithmic.Learning is a dynamic and iterative process for modifying the parameters of a network in response to the stimuli it receives from its environment. The type of learning is determined by how parameter changes occur. In this article , we contribute to the design and development of an algorithm, that can optimize the parameters of a PID controller for the control of repetitive system, using the iterative learning approach based on neural network. The theoretical are illustrated by simulation. The results of simulations prove clearly the efficiency of the control by iterative learning based on neural network .*

Streszczenie. *Uczenie się iteracyjne odnosi się do rozwoju, analizy i wdrażania metod, które pozwalają maszynie rozwiązywać problem w procesie uczenia się, a tym samym wykonywać zadania, które są trudne lub niemożliwe do wykonania przy użyciu bardziej konwencjonalnego algorytmu. Rodzaj uczenia się zależy od tego, jak zachodzą zmiany parametrów. W tym artykule zaprojektowano i opracowano algorytmu, który może zoptymalizować parametry regulatora PID, wykorzystując podejście iteracyjnego uczenia się w oparciu o sieć neuronową. Wyniki symulacji jednoznacznie dowodzą skuteczności sterowania poprzez iteracyjne uczenie się w oparciu o sieć neuronową. (**Sterowanie PID przy wykorzystaniu uczenia iteracyjnego bazującego na sieciach neuronowych**)*

Keywords: learning process, PID controller, dynamic process, CSTR
Słowa kluczowe: uczenie iteracyjne, regulatory PID, sieci neiuronowe

Introduction

When the desired trajectory is repetitive or periodic, the control system will make the same errors from iteration to the other one. Indeed, the control system does not take into account errors made during the previous iterations. So, it would be interesting to use all the information obtained on the control system during the previous iterations to improve the pursuit of the desired trajectory. This basic idea gave rise to the iterative learning control(ILC). The concept of ILC was originally pioneered in the work of [1], although the field began to take the present shape starting with the works of [2] and others[3,4]. ILC is a feedforward signal design technique that iteratively fine-tunes and adjusts the feedforward signal by considering the error from previous iterations of the repetitive process. In other words, we iteratively reshape the input signals to the closed-loop system from one run to another to reduce tracking error. This method requires that the repetitive process have specified start and finish states [5-6]. ILC is intended for discontinuous operation. For example, an ILC application might be to control a robot that performs a task, returns to its home position, and comes to rest before repeating the task. ILC has been implemented in several industrial processes because of its simplicity of design, analysis, and implementation, typical applications of ILC include industrial robotics, rapid thermal processing, metal rolling, and wafer scanning. Along with applications, many ILC algorithms that guarantee better robustness, performance, and faster rates of convergence have been developed.

PID controllers were empirically regulated by the methods described by Ziegler and Nichols (1942) [7]. They have proposed two experimental approaches to adjust the parameters of the PID. The first solicits the registration of the step response of the system to be regulated in an open loop, and the second requires to bring the closed-loop of the system to its limit of stability. Which must have very low damping, typically ξ=0.2. PID controllers can yield accurate position control arduous as the ξ is increased[8-9]. For the desired improvement in control, it is necessary To use methods other than the traditional PID controller [7]. The intelligent control method represented by a neural network can perform arbitrary functions with arbitrary precision and a self-learning function. neural networks are applied to the design of the control system for its ability to manage, the non-linearity, uncertainty, and complexity of the system. And due to the adaptability, the parallel processing capability and the robustness of the neural network, the control system using the neural network has superior adaptability and robustness[9]. The traditional PID controller has the advantages of a simple structure, convenient adjustment and a close connection between parameterization and technical indicators. However, the traditional PID controller also has some limitations: when the parameters of the plant are nonlinear, the controller settings are automatically adjusted to accommodate changes in the plant, and it is difficult to change the time and the time of some complicated processes and parameters [8]. So it is easy to compensate for the disadvantages of conventional PID control. The combination of conventional PID control with neural networks is a trend of modern control theory [10-14].

The remainder of this paper is structured as follows: section II presents the basic theory of PID control, including the characteristics of the algorithm. Section III exposes the problem, followed by the tuning methods studied which are: PID based on neural network, and PID parameters by iterative learning based on neural network. in Section IV. The simulation for two approaches is presented. And a conclusion is done in section V.

basic theory of PID control

The PID controller consists of three steps: proportional, integral, and differential. Its mathematical description is:

$$u(t) = k_p e(t) + k_i \int_0^t e(\tau) d\tau + k_d \frac{de(t)}{dt} \quad (1)$$

where : u(t) is the output value; e(t) is the tracking error signal; k_p is the proportionality factor; k_i is the integral time constant; and k_d differentiate the time constant.

Digital PID controller:

In the computer control system, a digital PID controller is used and the digital PID control algorithm is generally divided into a position PID control algorithm and an incremental PID control algorithm. according to (1) of the analog PID control algorithm, the continuous-time t is represented by a series of sampling time points, the integral is replaced by the sum, the differential is replaced by the increment and the following approximate transformation can be performed:

(2) $$\int_0^t e(t)dt \approx T \sum_{j=0}^{k} e(jT) = T \sum_{j=0}^{k} e(j)$$

where t=kT, and k=0,1,2,3,4,5,..

T represents the sampling period.

(2.1) $$\frac{de(t)}{dt} \approx \frac{e(kT) - e[(k-1)T]}{T} = \frac{e(k) - e(k-1)}{T}$$

By Substituting equation (2.1) and (2.1) in (1),we obtain a discrete expression of the PID:

(2.2) $$u(k) = K_p e(k) + K_I \sum_{j=0}^{k} e(j) + K_D[e(k) - e(k-1)]$$

where $e(k)$ denotes the error at trial k, and $u(k)$ denotes the input at trial k . $u(k)$ is the control signal at the $k-the$ iteration while $e(k) = y_d(k) - y(k)$ is the tracking error signal between the actual output trajectory $y(k)$ and the desired one $y_d(k)$.

PID neural network controller:

The neural network is a non-linear function of several variables. This feature has many parameters labeled weight, adjusted by the learning procedure so that the function matches the desired data such as described in fig.2. Neural network-based PID control does not use neural networks to set PID parameters but uses neural networks directly as controllers, and indirectly adjusts PID parameters by training neural network weight coefficients. The neural network applied to the PID control is associated with the traditional PID controller, for improvement and optimization of the traditional PID control described by equation(1). According to (1) and (2.2), a single neuron is used to build the PID controller, as shown in Figure 1

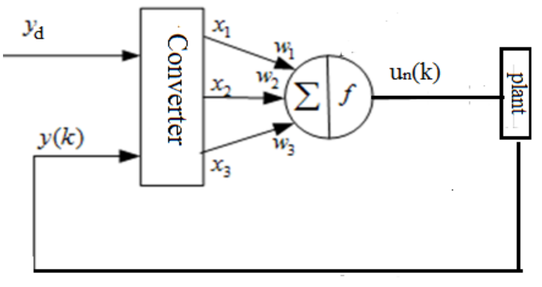

Fig.1. PID neural network controller

here :

$$X_1(k) = e(k)$$

(2.3) $$X_2(k) = \sum_{j=0}^{k} e(j)$$

$$X_3(k) = \Delta e(k) = e(k) - e(k-1)$$

The network output is:

(2.4) $$u_n(k) = w_1 X_1(k) + w_2 X_2(k) + w_3 X_3(k)$$

where W1, W2, and W3 are the weighting factor of the neuron, which is equivalent to the proportional, integral, and differential coefficients of the PID controller. the w_i parameter can be fixed online. By continuously adjusting it to reach an optimal value, the system's control performance can be improved. tests that are commonly performed in the industry. They include the Step, Pulse, Pseudo-Random Binary , and Doublet.

Iterative learning control

The configuration of the learning controller system will operate as follows. During the $(n-1)^{th}$ trial an input signal $u_{n-1}(t)$ is applied to the plant, producing the output signal $y_{n-1}(t)$. In the meantime, these two signals are stored in a memory buffer. At the end of this trial a new input signal, $u_n(t)$, is computed by an ILC algorithm. The ILC algorithm computes a new input signal which is dependent on the tracking error $e_{n-1}(t)$ and the previous input signal $u_{n-1}(t)$. The new input can be used in the next trial. The importance of the modification of the input signal is to reduce the tracking error $e_n(t)$. Mathematically expressed, this means that the control input $u_n(t)$ at the $(n)^{th}$ trial to the plant is given as a function of previous inputs and errors.

(3) $$u_n = f(u_{n-1}, e_{n-1})$$

where

$$u_n(t) = u_{n-1}(t) + k_p e_{n-1}(t) + k_i \int_0^t e_{n-1}(\tau)d\tau + k_d \frac{de_{n-1}(t)}{dt}$$

Neural learning controller:

By combining the two methods, iterative learning, and neural network**,** to adjust the parameters in real-time as is illustrated in fig.2, the state of the controlled system is represented by y_n (t) and the desired output by y_d(t). The outputs of the neural controller correspond to the states required for learning in the neural plane. The control signal is generated by the neurons via the activation function and self-learning. The neural network PID is added to the ILC controller to adjust the gains of the PID parameters on-line according to the change of the error signal.

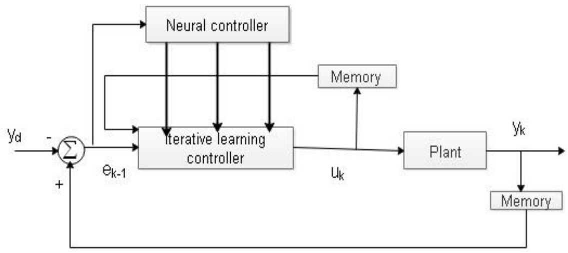

Fig.2. Bloc diagramme of Neural learning controller

The update law derived from the diagramme presented in the above figure is:

(3.1) $$u(k) = u(k-1) + K[w_1(k)x_1 + w_2(k)x_2 + w_3(k)x_3]$$

where :

$$k_p = K.w_1(k),\ k_d = K.w_2(k), \text{and},\ k_I = K.w_3(k).$$

Simulations illustrations

The CSTR continuous agitation reactor is the primordial element of many plants in the chemical industry, ill. The quality of control is affected mainly by the lack of a sufficiently clear understanding of the reaction mechanism, as well as the sensitivity, and the non-linearity of the process itself. The CSTR is a cylindrical tank with a diameter approximately equal to its length and a turbine for the stirring action. the level of mixing caused by the stirring action characterizes the quality of the CSTR. The CSTR parameters and their nominal operating condition are listed in the table1. If the input of the reactor is a periodic function, the output of the reactor is also a periodic function[15-16]. The learning control law described in this work is applied to manipulate the jacket temperature (Tj) of CSTR, to keep the system temperature at the desired level.

Table 1:cstr parameters

CSTR Parameters	Nominal operating condition
Feed concentration (CA0)	1 mol/l
Feed temperature (T)	350 K
Inlet coolant temperature (T_{CO})	350 K
CSTR volume (V)	100l
Heat transfer term (h/A)	7x105cal/(min K)
Reaction rate constant (k0)	7.2x1010 min^{-1}
Heat of reaction (DH)	2x105 cal/mol
Liquid density 9r, rc)	103g/l
Specific heats 9C_p, C_{pc})	1 cal/gk
Process flow rate (q)	100 l/min
Action energy term (E/R)	1x104k

CSTR dynamic Equation

The equilibrium equation of a chemical reaction in CSTR is given by:

(4) $(input) + (generation) = (output) + (accumulation)$

For a perfect mixing and constant volume is maintained in the jacket and reactor, the accumulation term is zero, and the state variable form of the dynamic equation can be derived by considering the mass and energy balance equations [13-14]. The CSTR model and the state space form are represented by the following equations :

(5a,b)

$$\frac{dC_A}{dt} = \frac{F}{V}(C_{Ai}\text{-}C_A)\text{-}k_0 e^{\frac{-E}{RT}} C_A$$

$$\frac{dT}{dt} = \frac{F}{V}(T_i - T) + (\frac{-\Delta H}{\rho C_p}) k_0 e^{\frac{-E}{RT}} C_A - \frac{U_A}{V\rho C_p}(T - T_j)$$

where the state x(t) and input u(t) vectors are given by x(t)=[C_A;T] and u(t)=[T_j].

Therefore, the state space and the input matrices are calculated as shown below:

$$A = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} \end{bmatrix} = \begin{bmatrix} -\frac{F}{V} - k_0 e^{\frac{-E}{RT}} & k_0 e^{\frac{-E}{RT}} (\frac{E}{RT^2}) C_A \\ -\left(\frac{\Delta H}{\rho C_p}\right) k_0 e^{\frac{-E}{RT}} & -\frac{F}{V} - \left(\frac{UA}{V_p C_p}\right) k_0 e^{\frac{-E}{RT}} (\frac{E}{RT^2}) C_A \end{bmatrix};$$

(5c) $$B = \begin{bmatrix} \frac{\partial f_1}{\partial u_1} \\ \frac{\partial f_2}{\partial u_1} \end{bmatrix} = \begin{bmatrix} 0 \\ \frac{UA}{V_p C_p} \end{bmatrix}, \text{and}$$

$$C = [0 \quad 1].$$

By substituting the nominals values, in the equation (5.C), we get the following state-space model :

$$A = \begin{bmatrix} -7.9909 & -0.013674 \\ 2922.9 & 4.5564 \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ 1.4582 \end{bmatrix}, C = \begin{bmatrix} 0 & 1 \end{bmatrix}, and$$

$$D = [0].$$

The transfer function expression and the step response without a controller of this process is done below:

$$G = \frac{1.4582S + 11.65}{S^2 + 3.434S + 3.557}.$$

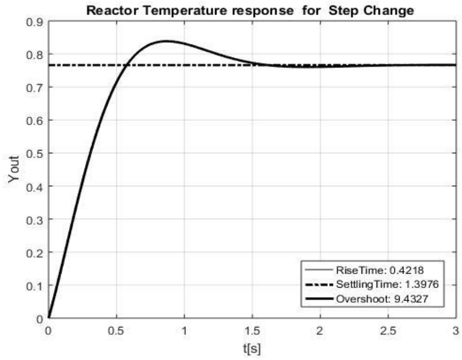

Fig. 3. system response for step change.

The designing of control parameters for this process is done by two approaches: neural network approach and neural ILC approach. The system response for a step input and error response with PID controller are first determined by neural network approach as shown in figure 4.

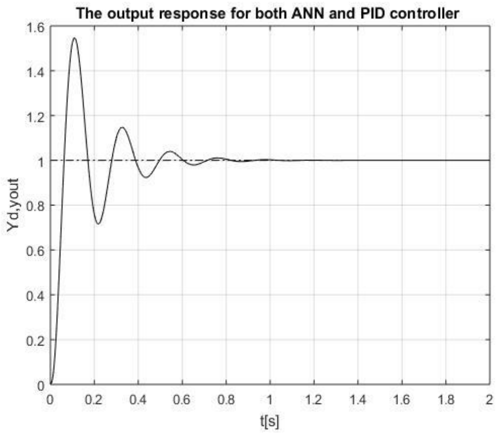

Fig..4.a. The output response

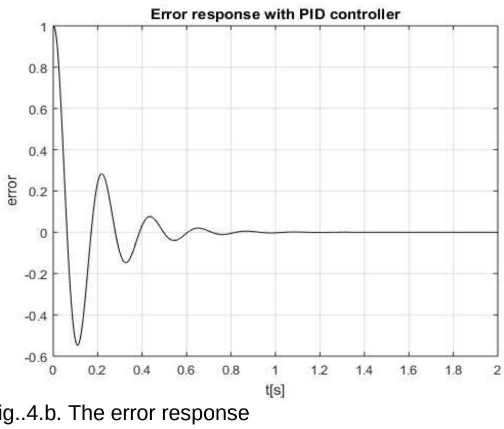

Fig..4.b. The error response

It can be seen that the jacket temperature follows the desired one with a significant reduction in the rise time and on the other hand an increase in the duration of the transient regime.

Applying the neural iterative learning control to the CSTR system described above, the simulation result for 6 trials are shown in fig.5, fig.6. It can be seen that the jacket temperature follows the desired one with a decreasing margin of error. The tracking error and transient behavior diminished when the number of iterations increases

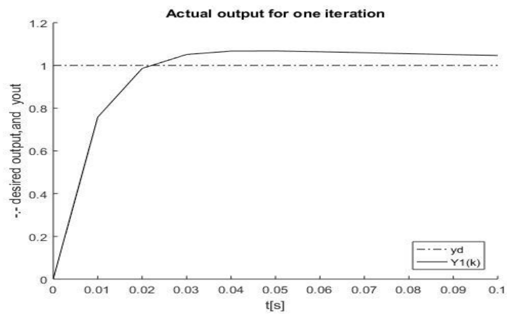

Fig.5.a. temperature response with one ILC iteration

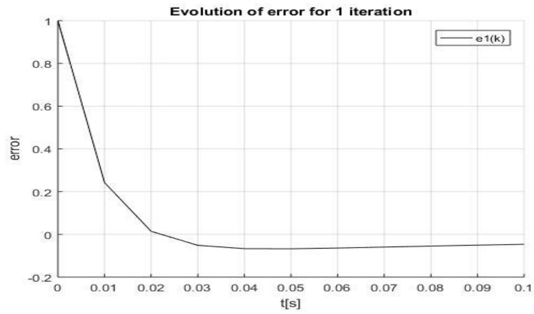

Fig.5.b.Evolution of error with one ILC iteration

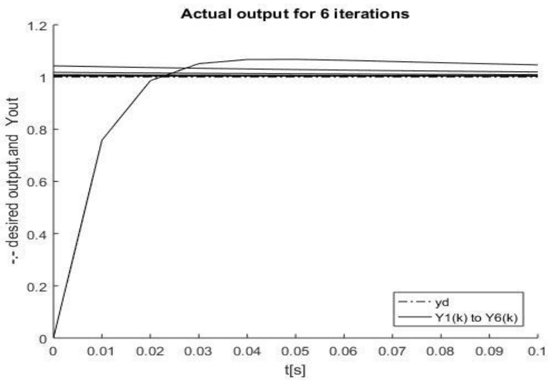

Fig.6.a.Temperature response for 6 iterations

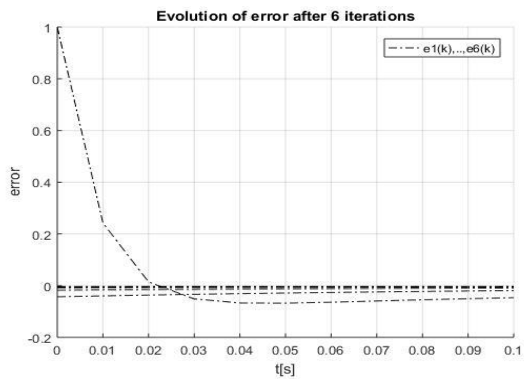

Fig.6. b.evolution of error for six iterations

Conclusions

The control of PID parameters based on the neural network, and iterative learning control for repetitive systems based on neural network are designed separately to achieve better system performance, and the results of the two methods are compared.

The neural network is used to produce Kp, Ki and Kd in real-time according to the control requirements, which in turn are used as real-time parameters of the PID controller, instead of manual tuning. As long as the difference between the current jacket temperature and the desired CSTR temperature is not zero, the neural network weight (w1, w2, and w3) is adjusted, then the PID parameters are adjusted to give less settling time and reduced overshoot compared to conventional PID and *PID* controller using *Metaheuristic* algorithms [17] .

The results of the simulation confirm that the systems in the initial state equal to zero and with a less rate, the convergence assured for a reduced number of iterations.

Authors:
Dr. Nora Karkar, Dr.Zarroug Nadjet, Dr.Tighilt Yamina, Pr.khier Benmhamed
E-mails:nkerkar@yahoo.fr,nadjatzerroug@yahoo.fr , tighilt_y@yahoo.fr, khierben@yahoo.com,
Faculty of engineering , Department of Electronic, University Ferhat Abbas of Setif, Algeria

REFERENCES

[1]Uchiyama, M. "Formation of high speed motion pattern of mechanical arm by trial",Journal of Society of nstrumentation and Control Engineers (Jpn),19,p.706-712,1978.

[2] S. Arimoto, S. Kawamura and F. Miyazaki, “Bettering operation of robots by learning”, *J. of Robot. Syst*.Vol. 1, No. 2, pp. 123-140, 1984. https://doi.org/10.1002/rob.4620010203.

[3]*G. Casalino* and G. Bartolini. *A learning procedure* for the *control of movements of robotic manipulators*. In IASTED symposium on robotics and automation, pp108-111,Amsterdam,Holland,1984.

[4] J.J.Craig "Adaptive Control of Manipulators Through Repeated Trials".Proc. American Control Conference, San Diego. June 1984, 1566-1573.

[5] M. Yu, X. Ye, and D. Qi, “Repetitive learning control for triangular systems with unknown control directions,” IET Control Theory & Applications, vol. 5, no. 17, pp. 2045–2051, 2011. doi: 10.1049/iet-cta.2010.0606.

[6]B.Richard,"application d’un algorithme de contrôle par apprentissage itératif à un four de thermoformage et identification des paramètres assurant l’uniformité de température",Master's thesis Montréal, 2012.

[7] PID Controllers: Theory, Design and Tuning, Second Edition, K.J Åström and T. Hägglund, Instrument Society of America, 1995.

[8]J.Li, A.Gómez-Espinosa "Improving PID control based on Neural Network", 2018 International Conference on Mechatronics, Electronics and Automotive Engineering (ICMEAE).DOI 10.1109/ICMEAE.2018.00042

[9]Kurser.Iha.dk,“ Ziegler Nichols method”,http://kurser.iha.dk/m/mtpri1/control/3_PID/f_ziegler/ziegler_nichols_method.html#Ziegler-Nichols_method,Published unknown date.Retreived 2018-05-14.

[10] E.Rogers, K. Galkowski,and D.H. Owens," Control Systems Theory and Applications for Linear Repetitive Processes", Springer-Verlag Berlin Heidelberg 2007.

[11]M.Muthuramalingam,P.S.Manoharan," Simulation and Experimental validation of Distributed MPPT algorithms for partially shaded Photovoltaic systems", Przegląd elektrotechniczny,2014.

[12]S.Chen,and J.T. Wen "Industrial Robot Trajectory Tracking Using Multi-Layer Neural Networks Trained by Iterative Learning Control",arXiv preprint arXiv:1903.00082, 2019.

[13]J. Liu," Intelligent control design and Matlab simulation", Tsinghua University Press, Beijing and Springer Nature Singapore Pte Ltd. 2018.

[14] Qian GAO, Guangxia LI," A Traffic Prediction Method based on ANN and Adaptive Template Matching", Przegląd elektrotechniczny,2011.

[15] M. M. Lund," Variable-volume operation of a stirred tank reactor", doctoral thesis ,lovia State University Of Science and Technology Ames, Iowa 1970.

[16] S. Anbu and M. Senthilkumar," Modelling and Analysis of Continuous Stirred Tank Reactor through Simulation",Asian Journal of Engineering and Applied Technology, ISSN 2249-068X Vol.7 No.1, 2018.

[17] S.Durgadevi and al," Comparative study of Controller Optimisation for CSTR using Particle Swarm Optimization Technique",ICEES 2019 Fifth International Conference on Electrical Energy Systems, 21- 22 February 2019, SSN College of Engineering, Chennai, India. DOI:10.1109/icees.2019.8719302.