Relay feedback test used for process identification and PID tuning controller by genetic algorithms

Identificación de procesos y sintonización de controladores PID mediante una prueba de relé usando un algoritmo genético simple

Rubén Lagunas-Jiménez,[1]* Manuel Benjamín Ortíz-Moctezuma,[2] Victor Moo-Yam,[1] Alonzo González-Aguilar[1]

[1] Facultad de Ingeniería, Universidad Autonoma de Campeche Campus V
Predio s/n por Av. Humberto Lanz Cardenas y Fracc. Ecologico Ambiental Siglo XXIII, col Ex Hacienda Kala. San Francisco de Campeche, Campeche. CP 24085
[2] Universidad Politécnica de Victoria
Av. Nuevas Tecnologias 5902, Parque Cientifico y Tecnologico de Tamaulipas, Carretera Victoria-Soto La Marina Km. 5.5. Ciudad Victoria, Tamaulipas. CP 87138
* Correo-e: jrlaguna@uacam.mx

KEYWORDS:

FFT, modeling, nonlinear least squares optimization, PID controller, genetic algorithm

ABSTRACT

In this article, a proposal to solve two control problems from multiple point identification process frequency response of linear models, using a relay closed loop is presented. The identified points are used, in one case a PID controller tuning, and the other application deals with transfer function modeling problem. Both problems are stated as a nonlinear least squares unconstrained minimization problem. The optimization problem is solved with a simple genetic algorithm.

PALABRAS CLAVE:

FFT, modelado, optimización no lineal, mínimos cuadrados, controlador PID, algoritmo genético

RESUMEN

En este trabajo se presentan dos problemas de control a partir de la identificación de múltiples puntos de la respuesta en frecuencia de sistemas lineales, mediante la técnica de relevador en lazo cerrado. En un caso, los puntos identificados son usados para la sintonización de controladores PID. La otra aplicación es hacia la obtención del modelo matemático mediante función de transferencia. Ambas dificultades son planteadas como un problema de minimización no lineal de mínimos cuadrados sin restricciones. El problema de optimización es resuelto con un algoritmo genético simple.

Recibido: 18 de enero de 2015• **Aceptado:** 5 de julio de 2015 • **Publicado en línea:** 30 de octubre de 2015

1 INTRODUCTION

Proportional-Integral-Derivative (PID) controllers are widely used in many control systems. In process control, more than ninety-five percent of the control loops are of PI or PID type [1, 2]. Since Ziegler and Nichols [3] proposed their empirical method to tune PID controllers, to date, many relevant methods to improve the tuning of PID controllers has been reported at the control literature, one of them is a tutorial given by Hang *et al.* [4].

The relay feedback auto-tuning method was proposed by Astrom and Hugglund [5], and was one of the first to be commercialized and has remained attractive owing to its simplicity. In this method, the estimation of critical point over nyquist curve is enough to tune a PID controller. In recently studies, it has been shown that the multiple identified points allow better PID tuning controller [6, 7]. This work presents two applications of the multiple-point identification method, reported by Wang *et al.* [6, 8], in order to tune PID controllers and, on the other hand, to obtain transfer function coefficients. The control problem is posed as a nonlinear least squares unconstrained problem.

A genetic algorithm is proposed to solve the optimization problem. The same methodology can be used for both cases: PID tuning and transfer function modeling. Nonlinear least squares methods involve an iterative improvement of parameter values in order to reduce the sum of the squares of the errors between the function and the measured data points. Problems of this type occur when fitting model functions to experimental data. The Levenberg-Marquardt algorithm [9-11], is the most common method for nonlinear least-squares minimization, nevertheless it can suffer from a slow convergence, and it is possible to find only a local minimum [10].

The PID's designed with this method takes into account the effect of the sensitivity function values of the closed-loop system as a measure of robustness against possible variations in the parameters of the plant [1]. The proposed plants in this article cover a wide range of cases: stable, with short and long dead times, whit real and complex poles, and with positive and negative zeros, which are representative of the automatic control literature [4, 5].

The contents of the paper are described as follows: In section 2 the basic definitions of a nonlinear least squares unconstrained minimization problem, use of relay transient as well as a simple genetic algorithm procedure are shown. Section 3 presents applications of the multiple point identification method to a PID controller tuning and to transfer function modeling. Conclusions are contained in section 4.

2 BASIC CONCEPTS

2.1 Unconstrained minimization problem

In a large number of practical problems, the objective function f (x) is a sum of squares of nonlinear functions

$$f(x) = \frac{1}{2}\sum_{j=1}^{m}(r_j(x))^2 = \frac{1}{2}\|r(x)\|_2^2 \quad (1)$$

that needs to be minimized. We consider the following problem

$$\min_x f(x) = \min_x \frac{1}{2}\sum_{j=1}^{m}(r_j(x))^2 \quad (2)$$

This is an unconstrained nonlinear least squares minimization problem. It is called least squares because the sum of squares of these functions is the quantity to be minimized. Problems of this type occur when fitting model functions to data: *if* $\varphi(x; t)$ represents the model function with t as an independent variable, then each $r_j(x) = \varphi(x; t_j) - y_j$, where $\varphi(t_j, y_j)$ is the given set of data points [10, 11].

2.2 Use of relay transient

It was shown by Wang *et al.* [6] who propose a method that can identify multiple points simultaneously under one relay test. Other important researches on the topic can be found at [12-15]. For a standard relay feedback system in figure 3, the process input *u(t)* and output *y(t)* are recorded from the initial time until the system reaches a stationery oscillation. *U(t)* and *y(t)* are not integrable since they do not die down in finite time. They cannot be directly transformed to frequency response meaningfully using *FFT*. A decay exponential e^{-at} is then introduced to form

$$\tilde{u}(t) = u(t)e^{-\alpha t} \quad (3)$$

and

$$\tilde{y}(t) = y(t)e^{-\alpha t} \quad (4)$$

such that *u(t)* and *y(t)* will decay to zero exponentially as *t* approaches infinity. Applying the Fourier transform to (3) and (4) yields

$$\tilde{U}(t) = \int_0^{\infty} \tilde{u}(t)e^{-jwt}\, dt = U(jw{+}\propto)$$

and

$$\tilde{Y}(t) = \int_0^{\infty} \tilde{y}(t)e^{-jwt}\, dt = Y(jw{+}\propto)$$

For a process *G(s)=Y(s)/U(s)*, at *s=jw+α*, one has

$$G(jw{+}\propto) = \frac{Y(jw{+}\propto)}{u(jw{+}\propto)} = \frac{\tilde{Y}(jw)}{\tilde{U}(jw)} \qquad (5)$$

Ỹ(jw) and *Ũ (jw)* can be computed at discrete frequencies with the standard *FFT* technique [6, 8]. Therefore, the shifted process frequency response *G(jw+α)* can be obtained from (5). To find *G(jw)* from *G(jw+α)*, we first take the inverse *FFT* of *G(jw+α)* as $\tilde{g}(kT)=FFT^{1}(G(jw+\alpha)) = g(kt)e^{-\alpha kt}$

It then follows that the process impulse response *g(kT)* is

$g(kt) = g(kt)e^{-\alpha kt}$

Applying the FFT again to g(kT) leads to the process frequency response:

$$G(jw) = FFT(g(kt)) \qquad (6)$$

The method can accurately identify as many as desired frequency response points with one relay experiment. They may be very useful for improving the performance of PID and other model-based controllers. The required computations are more involved than the standard relay technique, especially if a large number of frequency response points are needed. In both applications: PID tuning and transfer function modeling, the shifted frequency response may be used without the needing to computer *G(jw)*. To illustrate the method, a model with oscillatory dynamics is considered in simulation.

$$G(s) = \frac{1}{s^2{+}.2s{+}1}e^{-.2s} \qquad (7)$$

Figure 1 shows the identified frequency responses for these processes using this method, for *G(jw)*.

And *G(jw+α)* plot is given by figure 2.

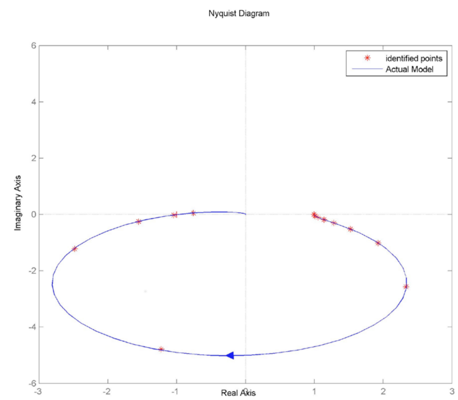

Figura 1. Nyquist plot for *G(jw)*

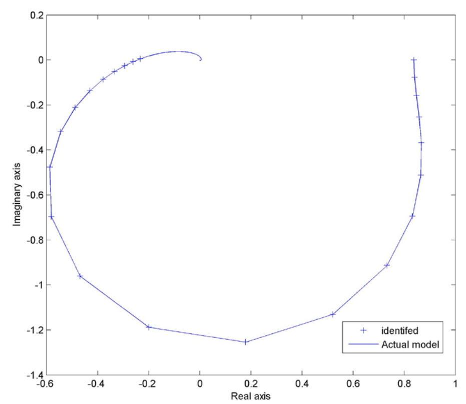

Figura 2. Nyquist plot for *G(jw+α)*

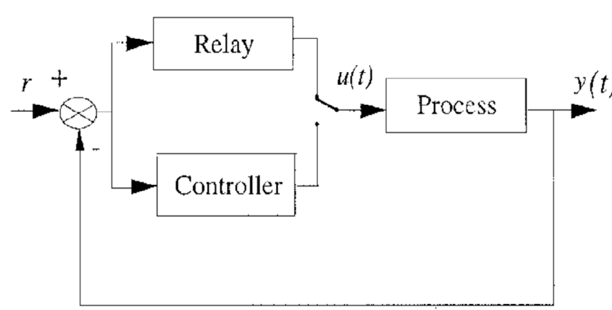

Figura 3. Relay feedback system

2.3 Simple Genetic Algorithms

The genetic algorithm is a useful tool to solve both constrained and unconstrained optimization problems that takes principles of biological evolution [16-19]. The following procedure summarizes the main steps that the genetic algorithm executes:

1. The algorithm starts by creating a random initial population.
2. The algorithm then creates a sequence of new populations. At each step, the algorithm uses the individuals in the current generation to create the next population. To create the new population, the algorithm performs the following steps:

a. Assign a grade to each member of the current population by computing its fitness value.
b. Selects members, called parents, based on their fitness.
c. Some of the individuals in the current population that have better grades are chosen as elite. These elite individuals are passed on to the next population.
d. Children from the parents are produced by means of crossover and mutation operators.
e. The current population is replaced with the children to form the next generation.

3. The algorithm stops when one of the stopping criteria is met.

3 APPLICATIONS

3.1 PID Tuning via frequency response fitting

PID Tuning via frequency response fitting is a simple but efficient solution to this kind of processes that was developed [4]. It shapes the loop frequency response to optimally match the desired dynamics over large range of frequencies. Thus the closed-loop performance is more firmly guaranteed than in the case of only one or two points PID or PI tuning laws. Suppose that multiple process frequency response points *G(jwi), 1=1,2,...,m*, are available. The control specifications can be formulated as a desirable closed loop transfer function

$$H_d(s) = \frac{\omega_n^2}{s^2+2\zeta\omega_n+\omega_n^2}e^{-Ls} \quad (8)$$

where L is the apparent *dead-time of the process*, *wn* and ζ dominate the behavior of the desired closed-loop response, [4]. If the control specifications are given as the phase margin Φ_m, and gain margin A_m, w_n and ζ in H_d are approximately determined by

$$\zeta = \sqrt{\frac{1-cos^2(\phi_m)}{4cos^2\phi_m}}$$

and

$$\omega_n = \frac{\tan^{-1}(\frac{2\zeta p}{p^2-1})}{pL}$$

where p is the positive root of equation

$$(A_m-1)^2 = 4\zeta^2 p^2 + (1-p^2)^2$$

The default settings for ζ and w_nL values are *=707* and $w_nL=2$, which imply that the overshoot of the objective set-point step response is about 5%, the phase margin is 60° and the gain margin is 2.2 [20]. The open-loop transfer function corresponding to G_d is

$$G_d = \frac{H_d}{1-H_d} \quad (9)$$

The controller *C(jw)* is designed such that the actual *GC(jw)* is fitted to the desired transfer function $G_d(jw)$, as well as possible. Thus the resultant system will have the desired performance. The PID controller desired can be obtained by minimizing the objective function given from the sum of squared differences between computed and recorded frequency response points

$$CG(jw_i) = \frac{Kpjw_i+Ki+Kd(jw_i)^2}{jw_i}G(jw_i) \quad (10)$$

$$G'_d(jw_i) = \begin{bmatrix} Real(G_d(jw_i)) \\ Imag(G_d(jw_i)) \end{bmatrix}$$

$$CG'(jw_i) = \begin{bmatrix} Real(GC(jw_i)) \\ Imag(GC(jw_i)) \end{bmatrix}$$

The objective function

$$y = \sum_1^m |CG'(jw_i) - G'_d(jw_i)|^2 \quad (11)$$

If the PID controller is designed from *G(jw+α)*, then

$$C(jw_i+\alpha) = \frac{Kp(jw_i+\alpha)+Ki+Kd(jw_i+\alpha)^2}{(jw_i+\alpha)} \quad (12)$$

$$CG(jw_i+\alpha) = C(jw_i+\alpha)G(jw_i+\alpha)$$

$$CG'(jw_i+\alpha) = \begin{bmatrix} Real(GC(jw_i+\alpha)) \\ Imag(GC(jw_i+\alpha)) \end{bmatrix}$$

$$G'_d(jw_i+\alpha) = \begin{bmatrix} Real(G_d(jw_i+\alpha)) \\ Imag(G_d(jw_i+\alpha)) \end{bmatrix}$$

The objective function

$$y = \sum_1^m |CG'(jw_i + \alpha) - G'_d\,(jw_i + \alpha)|^2 \quad (13)$$

The solution of the problem is obtained by minimizing y.

In this work, the identified points were obtained from a schematic Simulink® system where relay feedback system is simulated. To solve the optimization problem, the MATLAB® genetic algorithm optimizations using the optimization tool GUI is used.

Example 1. Consider a model with oscillatory dynamics

$$G(s) = \frac{1}{s^2 + .2s + 1} e^{-.2s} \quad (14)$$

The identified points for this model are showed in figures 1 and 2. In this example the apparent dead-time $L=0.2$, is proposed.

The designed PID is solved by minimizing the equation 11 by means of a simple genetic algorithm. Multiple points are from *G(jw)*

$$C(s) = (0.598 + \frac{2.94}{s} + 2.96s] \quad (15)$$

And from *G(jw+α)*, the tuned PID is

$$C(s) = (0.6 + \frac{2.94}{s} + 2.998s] \quad (16)$$

Eq, (15)-(16) show that both PID's controllers have very close values as might be expected.

Performance of the PID designed is shown in the figure 4.

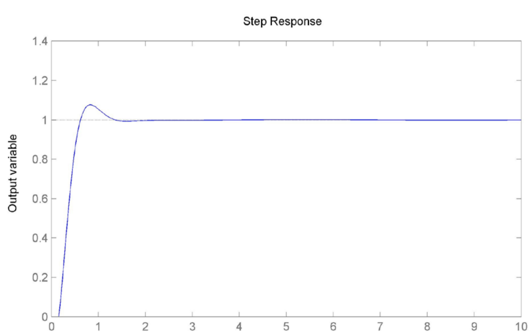

Figura 4. Control performance for an oscillatory process

Example 2. Considerer a high order model

$$G(s) = \frac{1}{(s+1)^{10}} \quad (17)$$

For this model the value of *apparent dead-time* of the process $L=4.5$ was proposed.

Estimated model from *G(jw)* the design PID is

$$C(s) = (0.922 + \frac{0.149}{s} + 2.62s) \quad (18)$$

Performance of the PID designed is shown in figure 5.

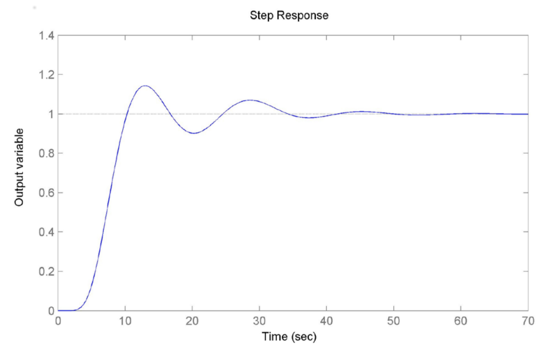

Figura 5. Control performance for high order model process

3.2 The sensitivity to modeling errors

Since the controller is tuned for a particular process, it is desirable that the closed loop system is not very sensitive to variations of the process dynamics [21]. A convenient way to express the sensitivity of the closed loop system is through the sensitivity function *S(s)*, defined as: $S(s) = \frac{1}{1+L(s)}$, where *L(s)* denotes the loop transfer function [2, 3,5,7,22]. *L (s)* is given by:

$$L(s) = C(s)G(s)$$

$$= G(s)k\left(1 + \frac{1}{T_i s} + T_d s\right)$$

The maximum sensitivity (frequency response) is then given by $M_s = \max_\omega |S(i\omega)|$. Therefore Ms is given by $M_s = \| S(s) \|_\infty$. On the other hand, it is known that the quantity M_s, is the inverse of the shortest distance from the Nyquist curve of loop transfer function to the critical point $s=-1$ [2]. Typical values of M_s are in the range from 1.2 to 2.0.

Table 1 shows the values of M_s, M_A and Φ_m for both presented examples, model with oscillatory dynamics and high order model.

The operation of genetic algorithm was configured with the following parameter values:

Tabla 1. Values of M_s, M_A and Φ_m

Model	M_S	Gain margin	Phase margin
$\frac{1}{s^2+.2s+1}e^{-.2s}$	1.65	2.2	60°
$\frac{1}{(s+1)^{10}}$	1.90	2.0	56°

- Population size: 100
- Stochastic uniform Selection
- Crossover function: Scattered
- Mutation function: Gaussian
- Number of generation: 500
- Crossover probability: 0.8
- Mutation probability: 0.09
- Elite count: 2

3.3 Transfer function modeling

A transfer function model is necessary in many applications of automatic control. In this work a second order plus dead-time model is proposed. The identification at models with dead-time is usually a non-linear problem [4, 8, 23]. This characteristic presents a good opportunity to apply a genetic algorithm to solve the problem.

$$G(s) = \frac{1}{as^2+bs+c} \tag{19}$$

Which can represent both monotonic and oscillatory processes.

3.3.1 Transfer function modeling from *G(jw)*

Suppose the process frequency response *G(jwi), i=1,2,…,M* is available, because they are required to be fitted into *G(s)* in (19) such that

$$G_m(j\omega_i) = \frac{1}{a(j\omega_i)^2+bj\omega_i+c}e^{-L\omega_i} \tag{20}$$

where *i=1,2,…,M*

then

$$G_m{}'(jw_i) = \begin{bmatrix} Real\big(G_m(jw_i)\big) \\ Imag\big(G_m(jw_i)\big) \end{bmatrix}$$

And the identified points of G(jw)

$$G'\,(jw_i) = \begin{bmatrix} Real(G(jw_i)) \\ Imag(G(jw_i)) \end{bmatrix}$$

The objective function is

$$y = \sum_1^m |G_m'\,(jw_i) - G'(jw_i)|^2 \tag{21}$$

The solution of the problem is obtained by

$$\min_i \sum_1^m |G_m'\,(jw_i) - G'(jw_i)|^2 \tag{22}$$

3.3.2 Transfer function modeling from *G(jw+α)*

Suppose the shifted frequency response of the process *G(jwi+α), i=1,2,…,M* is available, because they are required to be fitted into *G(s)* in (19) such that

$$G_m(j\omega_i{+}\propto) = \frac{1}{a(j\omega_i{+}\propto)^2+b(j\omega_i{+}\propto)+c}e^{-L(j\omega_i+\propto)} \tag{23}$$

where *i=1,2,…,M*

then

$$G_m{}'(jw_i+\alpha) = \begin{bmatrix} Real\big(G_m(jw_i+\alpha)\big) \\ Imag\big(G_m(jw_i+\alpha)\big) \end{bmatrix}$$

And the identified points of G(jw)

$$G'\,(jw_i+\alpha) = \begin{bmatrix} Real(G(jw_i+\alpha)) \\ Imag(G(jw_i+\alpha)) \end{bmatrix}$$

The objective function is

$$y = \sum_1^m |G_m'\,(jw_i+\alpha) - G'(jw_i+\alpha)|^2 \tag{24}$$

The solution of the problem is obtained by

$$\min_i \sum_1^m |G_m'\,(jw_i+\alpha) - G'(jw_i+\alpha)|^2 \tag{25}$$

Examples

Table 2 shows the results of some examples that were proposed to obtain the identified models from multiple points from *G(jw)* and *G(jw+α)*. The estimated models were solved by minimizing the equations (22) and (25) by means of a simple genetic algorithm.

Table 2. Proposed model processes

ACTUAL MODEL	ESTIMATED MODEL FROM *G(jw)*	ESTIMATED MODEL FROM $G(jw+\alpha)$
$\frac{1}{s^2+.2s+1}e^{-.2s}$	$\frac{1}{s^2+.2s+1}e^{-.197s}$	$\frac{1}{s^2+.2s+1}e^{-.199s}$
$\frac{1}{(s+1)^{10}}$	$\frac{1}{8.17s^2+5.02s+1}e^{-5.05s}$	$\frac{1}{8.2s^2+5s+1}e^{-5.05s}$
$\frac{-s+1}{(s+1)^5}e^{-2s}$	$\frac{1}{2.3s^2+3s+.99}e^{-5s}$	$\frac{1}{2.3s^2+3s+.99}e^{-5s}$
$\frac{1}{(10s+1)}e^{-2s}$	$\frac{1}{9.99s+1}e^{-2s}$	$\frac{1}{9.99s+1}e^{-2s}$
$\frac{1}{s^2+s+1}e^{-s}$	$\frac{1}{.99+s+1}e^{-1s}$	$\frac{1}{.999+s+1}e^{-1s}$

3.4 Transfer function modeling for processes with long dead-time

Processes with long dead-time are present in most of the industrial processes and can be adequately approximated by a model in form of

$$G(s) = \frac{K}{(Ts+1)^2}e^{-Ls} \quad (26)$$

Example 3 consider a high vacuum distillation column which is a typical long dead-time process [9]

$$G(s) = \frac{0.57}{(8.6s+1)^2}e^{-18.7s} \quad (27)$$

The identified model is given in Eq. (28). It was obtained by the same method as was presented previously. Figure 6 shows the identified points on the Nyquist curve from *G(jw+α)*.

$$\hat{G}(s) = \frac{0.571}{(8.6s+1)^2}e^{-18.71s} \quad (28)$$

In this example, the number of generations and population size used for genetic algorithm are: 1500 and 100 respectably.

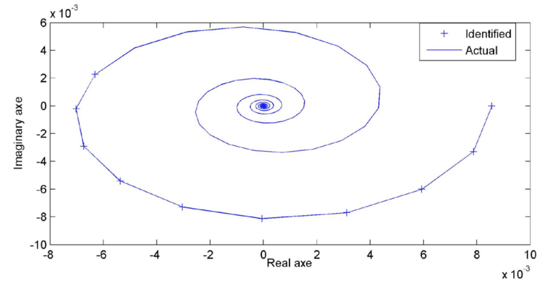

Figura 2. Nyquist plot for *G(jw+α)*

4 CONCLUSION

The genetic algorithm was an excellent tool to solve the optimization problem. It was very important that the same methodology can be used for both cases: PID tuning and transfer function modeling. In both applications, the results obtained were more accurate from the identified points of *G(jwi+α)* to *G(jwi)*. It was due to the fact that using *G(jwi+α)* is more direct than *G(jwi)*. Nonlinear least squares method was successfully applied in all cases to adjust the parameters values in order to reduce the sum of the squares of the errors between the function and the measured data points. It is remarkable that this method has a good performance to obtain a model with very long dead time, proposed in example 3, no matter that it used a different structure to that of the other cases.

It is also important to mention that Ms value was always a referent in relation to a good performance of the designed PID's, especially at the relative stability; on the other hand, when the Ms value is within the proposed range, this ensures that the controlled systems are insensitive to possible changes in plant models [1]. Therefore, the values of gain margin and phase margin were very close as expected.

On the other hand, in regard to the convergence of the genetic algorithm, it is known that in practice there is no way to know whether it has reached or not to the optimal solution (that applies any GA). A possible stopping criterion is the consecutive lack of new solutions that dominate the ones which are better up to the moment. If there is no progress after a certain number of iterations, it is reasonable to assume that the algorithm converged already, but obviously there is no guarantee of that.

REFERENCES

1. Åström, K.J., Hägglund, T. *PID Controllers: Theory, Design, and Tuning*. Instrument Society of America, Research Triangle Park, NC, 1995.
2. Jamshidi, M., Coelho, L., Dos Santos, R.A. Krohling, R.R., Fleming P.J. *Robust Control Systems with Genetic Algorithms*. CRC Press LLC, 2003.
3. Ziegler,G., Nichols, N.B. Optimum Settings for Automatic Controllers. *Trans. ASME*. 1942, 64(11), 759-768.
4. Hang, C.C., Åström, K.J., Wang, Q.G. Relay feedback auto-tuning of process controllers—a tutorial review. IFAC, *Journal of Process Control*. 2002, 12(1), 143–162.
5. Åström, K.J., Hägglund, T. Automatic Tuning of simple controllers with specification on phase and amplitude margins. *Automatica*. 1984, 20(5), 645-651.
6. Wang, Q. G. Process Frequency Response Estimation from Relay Feedback. *Control Eng. Practice*.1997, 5(9), 1293-1302.
7. Doyle, J., Francis, B.A., Tannenbaum, A.R., *Feedback Control Theory*. Macmillan Publishing Company, 1992.
8. Wang, Q.G., Chieh, C.C., Bi, Q. A Frequency domain controller design method. *Chemical Engineering Research and Design*. 1997, 75, 64-72.
9. Gavin, H. P. The Levenberg-Marquardt method for nonlinear least squares curve-fitting problems. Department of Civil and Environmental Engineering Duke University, 2013.
10. Griva, I., Nash, S.G., Ariela, S. *Linear and Nonlinear Optimization*, Second Edition. Society for Industrial Mathematics, 2009.
11. Transtrum, B., Sethna, J.P. Improvements to the Levenberg-Marquardt algorithm for nonlinear least-squares minimization, *Preprint submitted to Journal of Computational Physics*. 2012.
12. Liu, T., Wang, Q. G., Huang, H. P. A tutorial review on process identification from step or relay feedback test. *Journal of Process Control*. 2013, 23, 1597–1623.
13. Levy, S., Korotkin, S., Hadad, K., Ellenbogen, A., Arad, M., Kadmon, Y. PID autotuning using relay feedback. Electrical & Electronics Engineers in Israel (IEEE), 2012, 1-4.
14. Majhi, S. Relay based identification of processes with time delay. *Journal of Process Control*. 2007, 17(2), 93-101.
15. Padhy, P. K., Majhi, S. Relay based PI_PID design for stable and unstable FOPDT processes. *Computer & Chemical Engendering*. 2006, 30(5), 790-796.
16. Coello-Coello, C. A., Van Veldhuizen, D. A., Lamont, G.B. *Evolutionary Algorithms for Solving Multi-Objective Problems*. Springer, 2007.
17. Fleming, P. J., Purshouse, R.C. Genetic Algorithms in Control Systems Engineering. Department of Automatic Control Systems Engineering University of Sheffield, SI 3JD, Research Report No. 789, May 2001.
18. Goldberg, D. E. *Genetic Algorithms in Search, Optimization, and Machine Learning*. Addison Wesley, 1989.
19. Holland, J.H. *Adaptation in Natural and Artificial Systems*. Ann Arbor: University of Michigan Press, 1975.
20. Kristiansson, B., Lennartson, B. Robust tuning of PI and PID Controllers. *IEEE Control Systems Magazine*. 2006, 26(1), 55-69.
21. Lennartson, B., Kristiansson, B. Pass Band and High frequency Robustness for PID Control. *Proceeding of the 36th Conference on Decision & Control*. San Diego: 1997, 2666-2671.
22. Panagopoulos, H., Åström, K. J., Hägglund, T. Design of PID Controllers based on Constrained Optimization. *Proceedings of the American Control conference*. San Diego: 1999, 6(1), 3858-3862.
23. Zhou, K., Doyle, J.C. *Essentials of Robust Control*. Prentice Hall, 1998.

Acerca de los autores

José Rubén F. Lagunas-Jiménez received a diploma engineering degree in Communications and Electronics Engineering from ESIME-IPN and a PhD in automatic control from Cinvestav-IPN, México D.F. He is researcher and teacher at University of Campeche, México. His research includes multiobjective optimization using genetic algorithms and fuzzy control.

Benjamín Ortiz-Moctezuma received a diploma engineering degree in Mechanical Engineering from ESIME-IPN and a PhD in Automatic Control from Cinvestav-IPN, México, D.F. He is researcher and teacher at Polytechnic University of Victoria, Tamaulipas. Mexico. His research includes delay systems in automatic control.

Victor Moo-Yam received a diploma engineering degree in Electronics Engineering from University of Campeche and a PhD degree in Bioelectronics from Cinvestav-IPN, México D.F. He is researcher and teacher at University of Campeche, México. His research includes instrumentation and chemical sensors.

Alonzo E. González Aguilar is a senior student of Engineering in Mechatronics at University of Campeche, México.