Closed Loop Step test used for Process Identification and PID tuning controller by Genetic Algorithms

Identificación de Procesos y Sintonización de Controladores PID mediante una prueba de Escalón en Lazo Cerrado usando un Algoritmo Genético

Rubén Lagunas Jiménez, Benjamín Ortiz Moctezuma,Victor MooYam, Francisco Lezama Zarraga
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, CP. 24085, San Francisco de Campeche, Cam, México.
Universidad Politecnica de Victoria
Av. Nuevas Tecnologias 5902, Parque Cientifico y Tecnologico de Tamaulipas, Carretera Victoria- Soto La Marina Km. 5.5, Cd. Victoria, Tam. México, CP. 87138

E-mail: jrlaguna@uacam.mx, mortizm@upv.edu.mx,victmmoo@uacam.mx, frlezama@uacam.mx

PALABRAS CLAVE:

FFT, modelado, optimización, controlador PID, algoritmo genético.

RESUMEN

Los métodos de identificación y diseño de controladores PID a partir de múltiples puntos de la respuesta en frecuencia, presentan mejores resultados, en comparación con los que consideran un solo punto de la respuesta en frecuencia. Los puntos identificados, los cuales se obtienen mediante el método del escalón en lazo cerrado, se utilizan para el diseño de controladores PID, y para modelar sistemas lineales mediante función de transferencia, proponiendo la estructura de un sistema de segundo orden más un retardo. Ambos problemas son planteados como un problema de optimización no lineal de mínimos cuadrados sin restricciones. El problema de optimización se resuelve mediante un algoritmo genético simple.

KEYWORDS:

FFT, modeling, optimization, PID controller, genetic algorithm.

ABSTRACT

The Identification problem and PID controllers design by means of multiple points of the frequency response are more convenient than only one point of the frequency response. In this article a proposal to solve two control problems from multiple point identification process frequency response of linear models, using a closed loop step, is presented. The identified points are used, in one case a PID controller tuning is pointed out, and the other application deals with transfer function modeling problem, by means of a second order system plus time delay. Both problems are stated as a nonlinear least squares unconstrained optimization problem. The optimization problem is solved with a simple genetic algorithm.

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1 INTRODUCCIÓN

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].As is well known, the dynamics of a process can be known from the transient response, so when it gets the step response is possible to determine both the process gain and the process dynamics. Due to this statement, in this work, the frequency response is obtained from the step response in a close loop system. The size of the step can be as small as it has desired, this is a great advantage because it can apply a small step near the operation point, without significantly affecting process safety. Step response test have been widely used for model identification in the process industry [5], and has remained attractive owing to its simplicity. Several researchers have made important contributions on Control-oriented model identification methods [6, 7-8, 9-10]. A significant tutorial review on process identification from step or relay feedback was presented by Liu et al, [5], where the most important identification methods developed in the past three decades are surveyed. In the first proposals on auto-tuning methods, one estimated 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 [4-5]. This work presents two applications of the multiple-point identification method, 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 [11-12], is the most common method for nonlinear least-squares minimization, nevertheless it can suffer from a slow convergence, and it is possible to finds only a local minimum [12].

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 [1-2, 13-14]. The proposed plants in this article cover a wide range of cases: stable, with short and long dead times, whit real and complex poles, integrating process and with positive and negative zeros, which are representative of the automatic control literature [4, 13]. The contents of the paper are described as follows: In section 2 the basic definitions of a nonlinear least squares unconstrained minimization problem, and the use of close loop step transient test, 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

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

that needs to be minimized. We consider the following problem

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

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 φ(x; t) represents the model function with t as an independent variable, then each $r_j(x) = φ(x; t_j) - y_j$ where $φ(t_j, y_j)$ is the given set of data points [11-12].

2.2 Use of close loop step transient

It was shown by Wang et al. [15-16] who propose a method that can identify multiple points simultaneously under one relay test. For a close loop step transient system in Figure 1, the process input u(t) and output y(t) are recorded from the initial time until, the system reaches a steady value, after the transient step response. U(t) and y(t) are not integrable since they do not die down in finite time (at T_{ss} time). They cannot be directly transformed to frequency response meaningfully using

FFT. A decay exponential $e^{-\alpha t}$ is then introduced to form

$$\tilde{u}(t) = u(t)e^{-\propto t}$$

and

$$\tilde{y}(t) = y(t)e^{-\propto t}$$

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

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

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

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

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

(Y) and (jw) and U and(jw) can be computed at discrete frequencies with the standard FFT technique [15-17]. Therefore, the shifted process frequency response G(jw+α) can be obtained from (5). To find G(jw) from G(jw+α), we firts take the inverse FFT of G(jw+α) as

$$\tilde{g}(kT) = FFT^{-1}\big(G(jw{+}\propto)\big) = g(kt)e^{-\propto kt}$$

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

$$g(kT) = \tilde{g}(kT)e^{\propto kT}$$

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

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

Since the identification process is based on sampled values, it is convenient to think that the sequences under study are simply a period of infinite periodic succession. This fact justifies the application of the Discrete Fourier Transform (FFT).

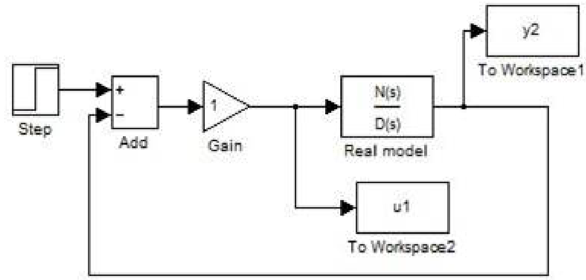

Figure 1. Schematic of feedback system

In this identification problem is very important the adequate selection of α value, in [18] a rule to compute the α value in terms of the Tss time (see Figure 2) is proposed, where the system reaches a steady value, after the transient step response. The value of α, it can be computed by means of:

$$\propto < \frac{1}{Tss} ln \frac{\Delta y(Tss)}{\delta}$$

Where Δy(Tss)=y(Tss)-y(0), denotes the dynamic output response in terms of the settling time (Tss) to the step change, in which y(0) indicates initial steady output value before the step test. δ is a computational threshold which may be practically taken smaller than Δy(Tss)x10-6

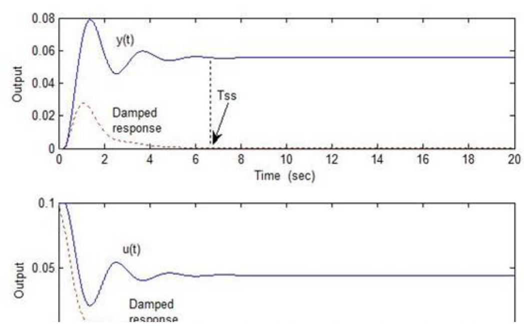

Figure 2. Signals under step feedback

The method can accurately identify as many as desired frequency response points with one step experiment. They may be very useful for improving the performance of PID and other model-based controllers. 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.

$$G(s) = \frac{1.25}{0.25s^2+.7s+1}e^{-.234s} \qquad (7)$$

Figure 3 shows the identified frequency responses for these processes using this method, for G(jw).

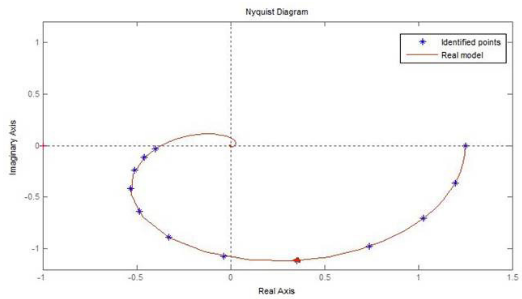

Figure 3. Nyquist plot for G(jw).

And G(jw+α) plot, where α=0.85, is given by Figure 4

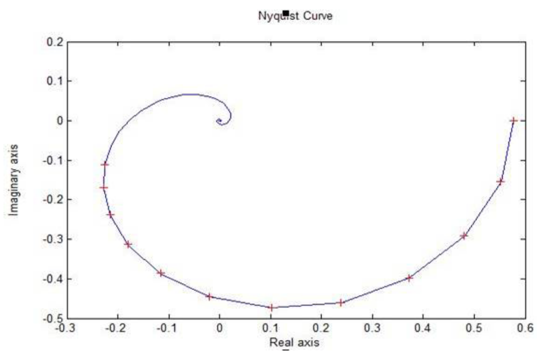

Figure 4. Nyquist plot for G(jw+α).

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 [14, 8, 19, 20-22,]. At present work, each of the individuals in the population (chromosomes), contain the parameters included in the fitness function, as an example, in the process to tune the PID controller, each chromosome contains the coded parameters of the controller [Kp, Ki, Kd].

3. Applications

3.1 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 in [4, 15-16]. 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, [9]. Specifications are given as the phase margin Φm, and gain margin Am. The default settings for ζ and wnL values are =0.707 and wnL=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 [4]. The open-loop transfer function corresponding to Gd 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 Gd(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

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

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

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

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

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

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

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

The objective function 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 the system feedback 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

$$G(s) = \frac{1.25}{0.25s^2+.7s+1}e^{-.234s} \qquad (14)$$

The identified points for this model are showed in Fig. (3)-(4). In this example the apparent dead-time L=0.23, is proposed.

The designed PID is solved by minimizing the equation 11 by means of a simple genetic algorithm. The PID parameters are coded and arranged into each individual (chromosome), of population in the genetic process. Multiple points are from G(jw)

$$C(s) = [1.453 + \frac{2}{s} + 0.561s] \qquad (15)$$

And from G(jw+α), the tuned PID is

$$C(s) = [1.45 + \frac{2}{s} + 0.561s] \qquad (16)$$

Equations (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 5. The time response shows that the overshoot value is close of 5%, as it was proposed.

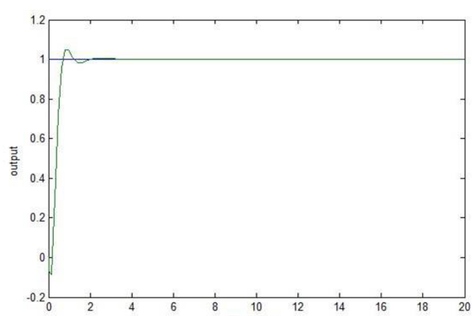

Figure 5. Control performance for an oscillatory process

Example 2. Considerer a high order model

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

For this model the value of apparent dead-time of the process L=4.5 was proposed. The modeling error for this example was 0.0097%

Estimated model From G(jw) the design PID is

$$C(s) = (0.808 + \frac{0.132}{s} + 1.99s) \qquad (18)$$

Performance of the PID designed is shown in the Figure 6

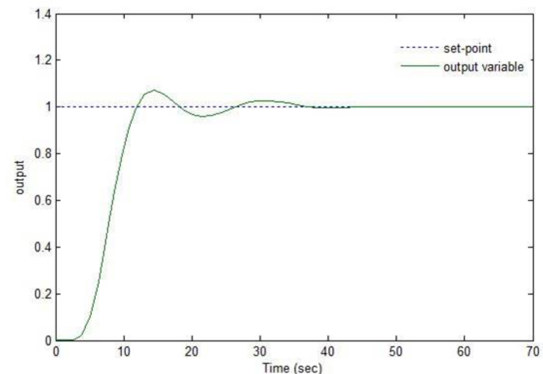

Figure 6. Control performance for high order model process.

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. 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 [13,22,14,16, 23]. 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 . Therefore Ms is given by Ms= $\|S(s)\|_{\omega}$. On the other hand, it is known that the quantity Ms, is the inverse of the shortest distance from the Nyquist curve of loop transfer function to the critical point s=-1 [13]. Typical values of Ms are in the range from 1.2 to 2.0.

$$M_s = \max_{\omega}|S(i\omega)|$$

Table 1 shows the values of Ms, Am and Φm for both presented examples, model with oscillatory dynamics and high order model.

Table 1. Values of *Ms*, A_m and Φ_m

Model	*Ms*	*Gain margin*	*Phase margin*
$\frac{1.25}{0.25s^2+.7s+1}e^{-.234s}$	1.685	3.13	59.4°
$\frac{1}{(s+1)^{10}}$	1.89	2.15	62.3°

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

- 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.

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

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

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

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

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

And the identified points of G(jw+α)

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

The objective function is

$$y = \sum_1^m |G_m'\ (jw_i+\alpha) - G'(jw_i+\alpha)|^2$$

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

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

Example 3

Table 2 shows five model in order to apply the proposed method. Table 3 shows the results of five 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. The Identified model parameters [a, b, c], are coded and arranged into each individual (chromosome), of population in the genetic process.

Table 2. Proposed models for example 3

Model number	Proposed model
1	$G(s) = \frac{1}{s^2+0.2s+1}e^{-0.2s}$
2	$G(s) = \frac{1}{(s+1)^{10}}$
3	$G(s) = \frac{-s+1}{(s+1)^5}e^{-2s}$
4	$G(s) = \frac{1}{(10s+1)}e^{-2s}$
5	$G(s) = \frac{1}{s^2+s+1}e^{-s}$

Table 3. Estimated models for example 3

Model	From G(jw)	From G(jw+α)
1	$\frac{1}{s^2+.2s+1}e^{-.197s}$	$\frac{1}{s^2+.2s+1}e^{-.199s}$
2	$\frac{1}{8.17s^2+5.02s+1}e^{-5.05s}$	$\frac{1}{8.2s^2+5s+1}e^{-5.05s}$
3	$\frac{1}{2.3s^2+3s+.99}e^{-5s}$	$\frac{1}{2.3s^2+3s+.99}e^{-5s}$
4	$\frac{1}{9.99s+1}e^{-2s}$	$\frac{1}{9.99s+1}e^{-2s}$
5	$\frac{1}{.99+1+1}e^{-1s}$	$\frac{1}{.999+1+1}e^{-1s}$

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 4

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 7 shows the identified points on the Nyquist curve from G(jw+α).

$$\hat{G}(s) = \frac{0.57}{(8.6s+1)^2}e^{-18.695s} \quad (28)$$

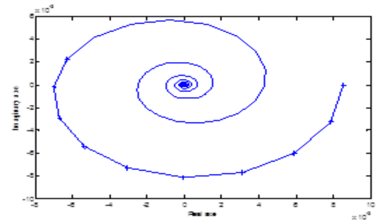

Figure 7. Nyquist plot for G(jw+α).

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

3.5 Transfer function modeling for integrating Processes with dead-time.

Integrating processes with dead-time can be adequately approximated by a model in form of SOPDT model, there is a commonly studied in the literature.

$$G(s) = \frac{K}{s(Ts+1)}e^{-Ls} \quad (28)$$

Example 5

Consider an integrating process plus a long dead-time [9]

$$G(s) = \frac{0.1}{s(20s+1)}e^{-10s} \quad (29)$$

The identified model is given in Eq. (30). It was obtained by the same method as was presented previously. Figure 8 shows the identified points on the Nyquist curve from G(jw+α).

$$\hat{G}(s) = \frac{0.1}{s(19.99s+1)}e^{-10.00} \quad (30)$$

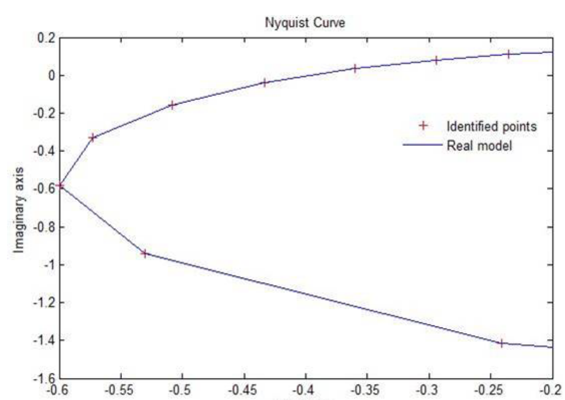

Figure 8. Nyquist plot for G(jw+α).

4. Conclusions

The genetic algorithm was an excellent tool to solve the optimization problem. It was very important that 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 to say that used method has a good performance to identify both models: very long dead time process and integrating process, proposed in Examples 4 and 5 respectively, no matter which use 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]. So it, the values of Gain Margin and Phase Margin were very close as expected.

On the other hand, with 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. This is the handicap of heuristic strategies.

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Acerca de los autores

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

BenjamínOrtizMoctezuma.Receivedthediplomaengineering degree in Mechanical Engineering from ESIME-IPN- and the PhD degree in Automatic Control from CINVESTAV-IPN, México, D.F. He is a Researcher and a teacher at Polytechnic University of Victoria, Tams. Mexico–. His research includes: Delay Systems in Automatic Control

VictorMooYam.Receivedthediplomaengineeringdegreein Electronics Engineering from University of Campeche - and the PhD degree in Bioelectronics from CINVESTAV-IPN, México D.F. He is a Researcher and a teacher at University of Campeche, México. His research includes Instrumentation and Chemical Sensors

Francisco Lezama Zarraga. Received the diploma engineering degree in Electrical Engineering from University of Campeche - and the PhD degree in Electrical Engineering from CINVESTAV-IPN, Jalisco. He is a Researcher and a teacher at University of Campeche, México