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An Experimental Study of the Empirical Identification Method to Infer an Unknown System Transfer Function

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Abstract: Identification is considered a very important procedure, within the control area, to estimate the best-possible approximate model among different designs. Its significance comes from the fact that more than 75% of the cost associated with an advanced control project is aimed at obtaining a precise mathematical modeling. Therefore, in this work, an exhaustive analysis was carried out to determine the appropriate input stimulus for an unknown real system that must be controlled, with the aim of accurately estimating its transfer function (TF) using the empirical identification method (gray-box). The analysis was performed quantitatively by means of three tests: (i) the PID controller step response was evaluated theoretically; (ii) the controller performance was assessed in a Cartesian robot by tracking a trajectory defined through a Gaussian acceleration profile; (iii) the efficiency of the determined input stimulus with the best performance on inferring the TF for the system to be controlled was verified by assessing its operation in a real system, through repeatability tests, utilizing the integral errors.

Keywords: experimental identification method; unknown system transfer function; system transfer function inference; PID control tuning; experimental study

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1. Introduction

System identification is an important area in control theory and can be defined as the art and science of building mathematical models of dynamic systems from observed input and output signals [1–3]. However, according to Gevers [4], identification is considered a procedure to estimate the best-possible approximate configuration within a set of models, in which, if the representation is exact, it will be optimal for any application. On the other hand, if the model is only an approximation of the true system, then the quality of the model will depend on the intended application. Therefore, whether a model is or is not appropriate for a control design depends on both the controller to be implemented and the mismatch between the plant and the model achieved through identification. However, although some research has been performed in the field of system identification over time, today, it continues being a developing area of interest to find a method that does not require prior knowledge of the system being controlled and whose versatility and approximation capacity are suitable for different applications [5,6].

Identification is one of the most-difficult subjects because of all the circumstances involved at the time of obtaining a real system transfer function, such as its order, the required input and the obtained output, its nonlinearities, as well as practical and economic limitations during experimentation, among many others [7]. Therefore, identification is an extremely important stage in the development of the control proposal because, if a good approximation model to the true system is not obtained, it will be more difficult to adjust the controller parameters to obtain the desired response. Hence, obtaining the expected result from the controller is highly related to the adequate identification of the transfer function for linear systems. In other words, identification is a process used to develop a suitable (mathematical) description for a system or process to be analyzed, controlled, or monitored.

In system identification theory, there are two contrasting approaches to identify the transfer function of a plant [8,9]. The first one is the theoretical approach (or white-box), which is based on the fundamental laws of matter and energy. To apply this technique, it is necessary to know each of the system components being modeled (electrical, mechanical, electronics, etc.) and their corresponding mathematical representation, to obtain the system's real transfer function [10,11]. The second approach is the empirical procedure (or black-box), which is based on analyzing the information obtained from the system by contrasting its input (test signal) against the corresponding produced output (response). In this case, the obtained data are examined through algorithms designed for estimating the parameters and coefficients of the transfer function that will represent the analyzed system. Although both methods are appropriate for determining a system transfer function, the empirical approach is more convenient since it relatively considers all the aspects involved in the process, such as vibrations, friction, and noise, among others, for determining the corresponding control strategy. However, there is a third method that combines the theoretical knowledge and the empirical or experimental approach, which is called the gray-box procedure [9]. The above-stated has great influence in industry since, typically, more than 75% of the costs associated with the development of an advanced control project are intended for inferring precise mathematical models [5,12]. On the other hand, it would be very difficult to take into consideration all the factors having an effect on determining a process transfer function through the theoretical approach in order to develop the corresponding control system.

Due to the importance of identifying the correct control system, different techniques have been developed, which have been classified into linear and nonlinear, according to the type of system being identified [6]. For linear system identification, different algorithms have been used for estimating the corresponding transfer function. For instance, in [13], the recursive least-squares (RLS), extended-RLS (ERLS), and Kalman filter (KF) methods are compared to identify a system transfer function with a sinusoidal input signal. In [14], adaptive filters such as the least-mean squares (LMS), the RLS, and the extended KF (EKF) were employed for identifying a system by means of a random input. In a similar approach, in [15–17], a system transfer function was inferred by applying the RLS and LMS adaptive filters utilizing a Gaussian-distributed random input signal. On the other hand, computational training and selection techniques are used commonly for nonlinear systems' identification. In [18–20], a nonlinear system estimation was carried out through fuzzy logic techniques, utilizing the difference between the determined and real system responses as the input signal. In [21,22], neural networks, particle swarm optimization (PSO), and genetic algorithms (GAs) were utilized for identifying a plant transfer function by means of sinusoidal and random input signals, respectively; however, an assessment study to confirm the compatibility between the attained model with the real one would be useful. Hence, from the above and taking into account the importance of the identification process to carry out the appropriate controller tuning for a linear system, it is evident that a comprehensive study about the significance of identifying a system transfer function properly, by means of distinct input stimuli, would be highly useful for adopting different mathematical models to represent the analyzed system dynamics.

Hence, in this work, an exhaustive experimental analysis to determine the input stimulus that provides the best transfer function (TF) estimate during the identification of a system plant through the empirical approach and theoretical approach (gray-box) is introduced. The deduced TF order is determined as well, which simplifies the tuning of a proportional–integral–derivative (PID) controller for managing the system operation. In this experimental study, the stepped and sinusoidal functions, as well as random signals were applied as input stimuli, with variations from the first to the third order on the inferred TF. Obtained results were validated by assessing the performance indices for the system to be controlled, through a statistical analysis, considering the distinct estimated TF with the attained PID controller tuning.

The document is elaborated as follows. First, the identification of the system and its evaluation criteria are presented. Second, the experimental setup is explained. Third, the comparison of the different stimuli as inputs for system identification is performed. Fourth, the experimental results are illustrated and discussed. Finally, conclusions are provided.

2. Identification System and Evaluation Criteria

2.1. System Identification

The process that leads to a system identification, utilizing the empirical or gray-box approach, consists of several stages that help to have a better estimation of the system transfer function. The procedure is shown in Figure 1. In the first step, the system input and output signals are acquired through experimentation and filtered to remove noise. Then, if there is prior knowledge about the system being modeled, the structural arrangement representing the system is chosen. In the second stage, signal-processing techniques are used for identifying the parameters or coefficients of the configured transfer function. The third and final step consists of validating the estimated transfer function for the inferred model, by determining the accuracy level reached by this suggested model regarding the true one.

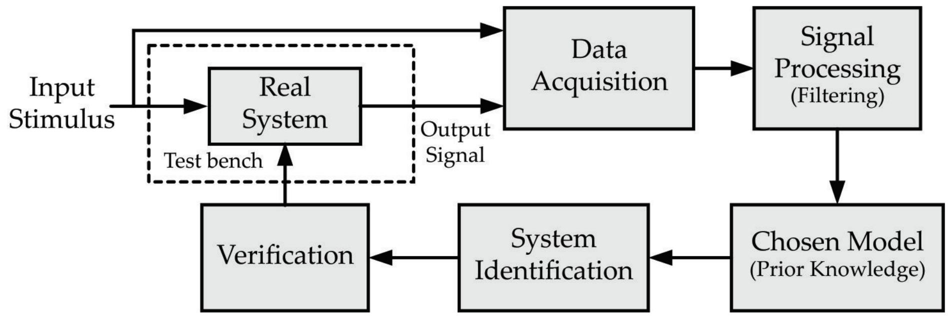

Figure 1. Identification-process flowchart.

If a satisfactory accuracy level is not reached for the model obtained by identification, it will be necessary to check the following aspects as possible causes: (i) the input and output datasets do not provide enough information about the system dynamics; (ii) the chosen structure is not capable of providing a good description of the real process; (iii) the selected parameter adjustment criteria are not appropriate. Consequently, the identification process can be considered as an iterative process, where the selected configuration parameters and excitation signal highly influence the system modeling accuracy.

2.2. Performance Evaluation

The identification process of a real system leads to having distinct estimates for its transfer function, since there are several circumstances that must be considered during its model determination, such as the choice of the system excitation signal, the processing techniques applied to the experimentation-acquired signals, the model structure selection, or the technique used for determining the TF coefficients, among many others. Being able to choose a system model involves the fact that the behavior of the inferred representation must closely mimic that of the real one; hence, quantitative indices are required for determining the performance of a tuned control system on the deduced model. The performance indices, such as the integral squared error (ISE), integral time squared error ($ITSE$), integral absolute error (IAE), and integral of time-weighted absolute value of error ($ITAE$), in addition to the nominal stability of the tuned control system determine if there is disturbance attenuation and if the reference point is being tracked correctly. These two conditions determine the tuned control system performance [23–25]. These different integral errors are measures for assessing the reference point tracking and the response of a tuned control system to disturbances. The integral errors used as criteria for evaluating the performance of a controller are defined in Equations (1)–(4).

$$IAE = \int_0^\infty |e(t)|dt \tag{1}$$

$$ISE = \int_0^\infty e(t)^2 dt \tag{2}$$

$$ITAE = \int_0^\infty t|e(t)|dt \tag{3}$$

$$ITSE = \int_0^\infty te(t)^2 dt \tag{4}$$

where the IAE determines small errors, the ISE determines large errors, and the $ITAE$ along with the $ITSE$ identify errors that persist for a long time.

3. Experimentation

3.1. Experimental Analysis Scheme

The exhaustive experimental analysis to verify the effectiveness of the proposed technique for identifying a system TF and the corresponding PID control tuning, through different input stimuli using the empirical method, is carried out in two stages: (i) the identification and (ii) the evaluation stages, which are depicted in Figure 2.

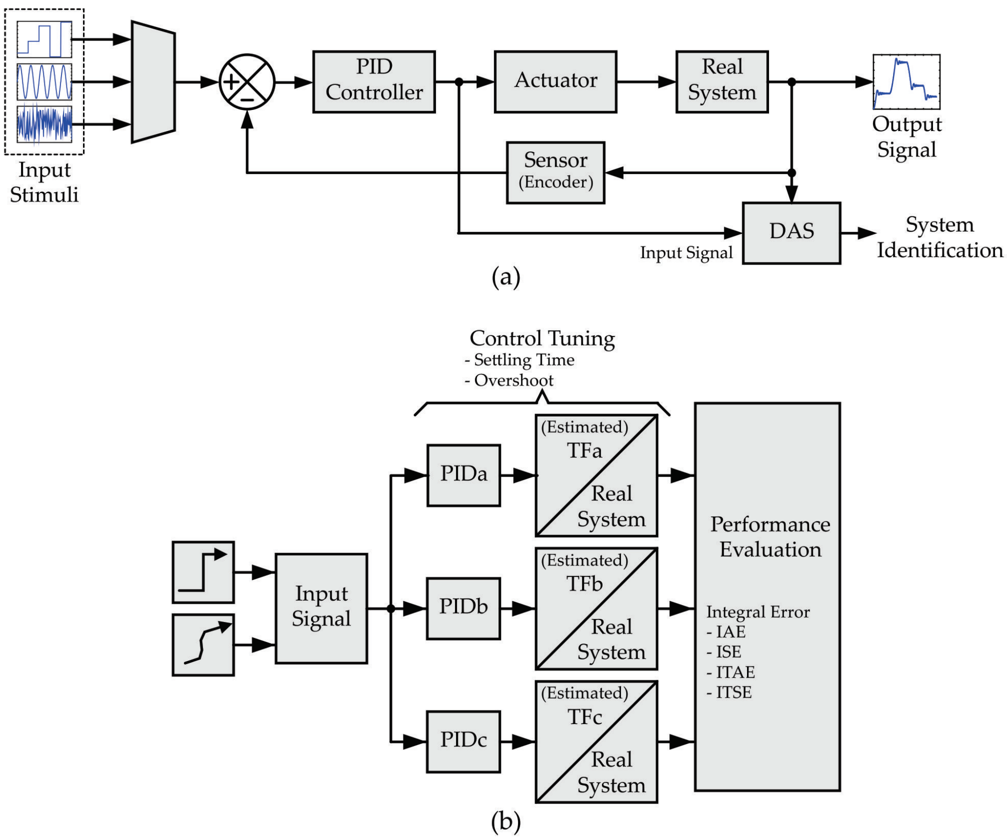

Figure 2. (**a**) System identification process and (**b**) performance evaluation of the system recognition, by applying distinct excitation input signals.

The system identification process, illustrated in Figure 2a, is carried out by applying the input excitation signals: (i) stepped signal, (ii) sinusoidal signal, and (iii) random signal. The PID controller in the closed-loop trajectory generates a gain on the actuator taking as a reference the error signal computed by the difference between the desired system position (input stimulus) and its real one (response measured with the sensor). In this regard, the position is a reliable and widely used reference in the industrial sector, which is commonly measured through an encoder; therefore, this study relied on controlling the system position for the system identification. Hence, the encoder indicates the system's real response, and a data acquisition system (DAS), embedded into a field programmable gate array (FPGA) [26], is used for carrying out the system identification utilizing the PID controller output and the system's real response, which are used for deducing three distinct TF (TFa, TFb, TFc) with their corresponding PID controller, as shown in Figure 2b; hence, the controller tuning will be simpler for the TF with the closet behavior to that of the real system [13].

The estimated TF assessment is performed through two analyses, as described in Figure 2b: (i) The performance of the PID controller is theoretically evaluated through the stepped signal response of the three estimated TFs. (ii) The controller performance is examined in a real system, utilizing as an input signal the trajectory generated through a Gaussian acceleration profile for a link of a Cartesian robot [27]. Three distinct PID controllers (PIDa, PIDb, and PIDc) are designed for each inferred TF, utilizing the root locus method for evaluating the system behavior, considering the system settling time and overshoot as the tuning parameters. Finally, the election of the input stimulus for the control system is quantitatively assessed through the integral errors criteria, described above in Section 2, and experimentally analyzed by tuning the PID controller to follow the trajectory defined for the system.

3.2. Proving Ground

The performance evaluation of the different input stimuli for identifying the appropriate control system was carried out utilizing a Cartesian robot, which is a key element in many different industrial processes that involve high-precision tasks, as shown in Figure 3. The experimental setup consisted of a servomotor (Model GYB41D5-RC2), with a 20-bit serial encoder, a servo driver (Model RYH401F5-VV2), and a Terasic DE0-CV development board with a Cyclone-IV FPGA device.

3.3. Identification

The identification process was carried out by exciting the x-link of the Cartesian robot through stepped, sinusoidal, and random signals, independently. The PID controller generates the input signal for each case of stimulus, as shown in Figure 4a–c, and the obtained system responses are shown in Figure 4d–f, correspondingly. From the PID-generated input signal, the system response signal, and the input stimulus, the identification process was performed to obtain three TF models: (a) first order, (b) second order, and (c) third order, for each input stimulus; these models are shown in Table 1. Figure 4g–i show the behavioral comparison of the real system against the three inferred TF models.

From the qualitative analysis depicted in Figure 4g–i, it can be observed that the second-order model approximation showed a close tracking of the input signal for the three cases of study, stepped, sinusoidal, and random stimuli. Hence, the root locus method was employed for tuning the PID controller utilizing the second-order system, considering the settling time and the maximum overshoot as design parameters, which are kept constant for all the PID controller designs, maintaining the same desired response for the different estimated system approximations.

3.4. Performance Assessment of PID Controller Tuning

It is evident that the best PID controller tuning is reached when the inferred TF closely resembles the real system dynamics. Hence, the purpose of the controller tuning is to estimate the proportional (k_p), derivative (k_d), and integral (k_i) gains by considering the PID controller's general definition given in (5).

$$C(s) = \frac{K_d s^2 + K_p s + K_i}{s} \tag{5}$$

The tuning process was performed utilizing the root locus method described on [28]; hence, the desired outcome was the same for all designs, maintaining a settling time of 1 s and an overshoot of 5%. A PID controller tuning was carried out for each system TF as described in (6)–(8), for the stepped, sinusoidal, and random stimuli, respectively. Figure 5a shows the desired behavior of the system and the obtained response for each different controller tuning. From this figure, it can be observed that all responses maintained a 5% overshoot, but their settling time changed depending on the PID controller tuning being utilized for the estimated TF.

$$C_{step}(s) = \frac{0.3783s^2 + 6.053s + 0.5961}{s} \tag{6}$$

$$C_{sine}(s) = \frac{0.52s^2 + 50.31s + 0.41}{s} \tag{7}$$

$$C_{rand}(s) = \frac{0.5104s^2 + 8.648s + 0.5935}{s} \tag{8}$$

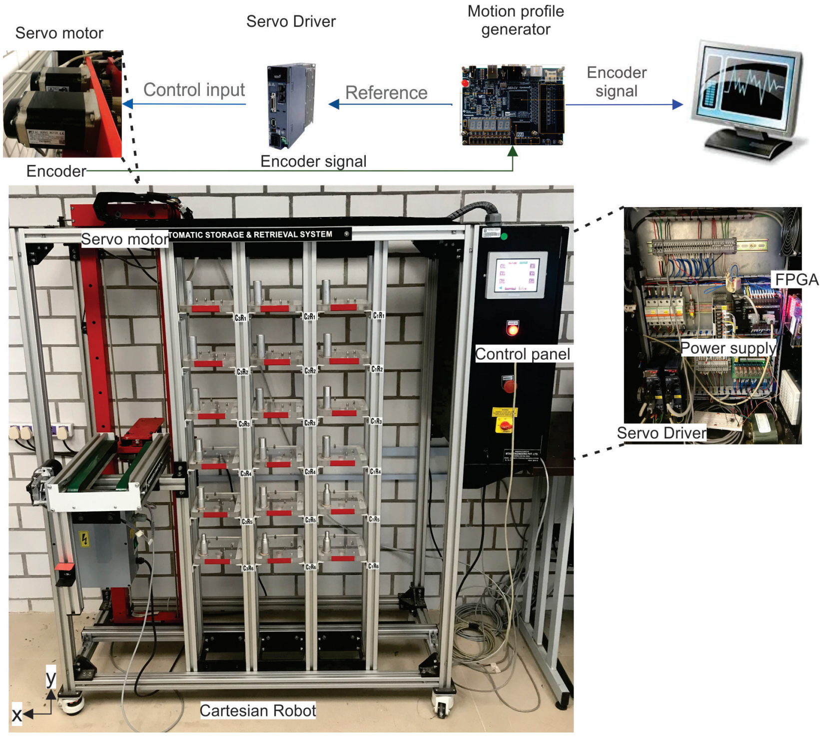

Figure 3. Experimental setup.

Table 1. Estimated transfer functions of the system utilizing different stimuli as inputs.

	STEPPED	SINE	RANDOM
$1st_{order}$	$G = \frac{82.541}{13.8225s + 1}$	$G = \frac{22{,}402}{139.42s + 1}$	$G = \frac{-0.022836}{1 + 1e^{-6}}$
$2nd_{order}$	$G = \frac{45.665}{0.7604s^2 + 7.377s + 1}$	$G = \frac{6930.6}{3.296s^2 + 29.42s + 1}$	$G = \frac{1124.8}{12.69s^2 + 122.6s + 1}$
$3rd_{order}$	$G = \frac{47.001}{0.018s^3 + 0.75s^2 + 7.7s + 1}$	$G = \frac{573{,}100}{75.2s^3 + 5578s^2 + 30{,}540s + 1}$	$G = \frac{1411.3}{0.3s^3 + 48.46s^2 + 204.86s + 1}$

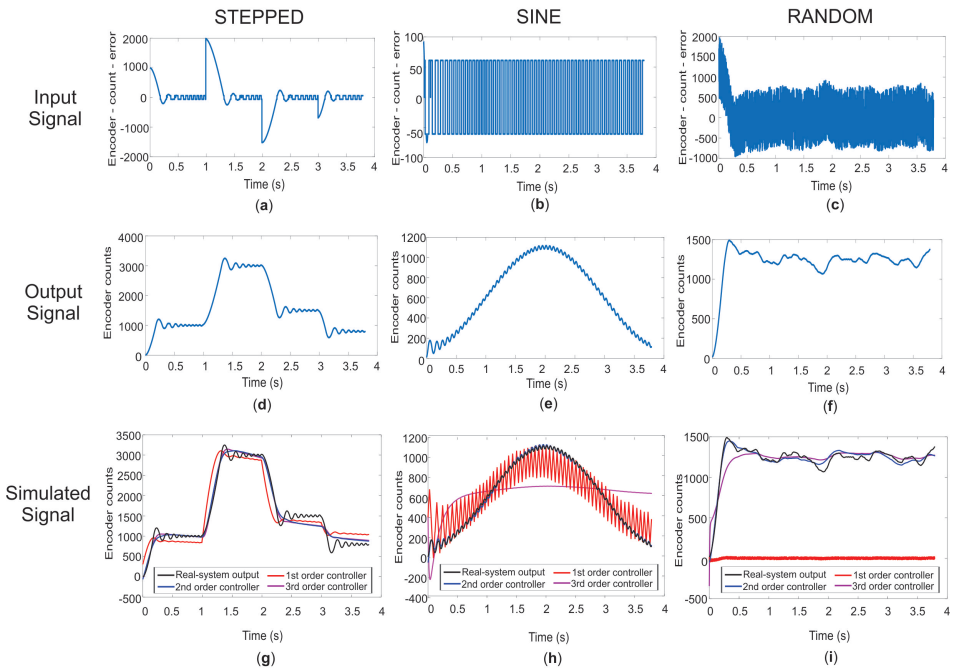

Figure 4. System identification process. (**a**) Stepped input, (**b**) sinusoidal input, and (**c**) random input stimuli. System output signals to the (**d**) stepped, (**e**) sinusoidal, and (**f**) random inputs. System response comparison of the real output signal measured against the computationally obtained responses of the different-order TFs for the (**g**) stepped, (**h**) sinusoidal, and (**i**) random input signals.

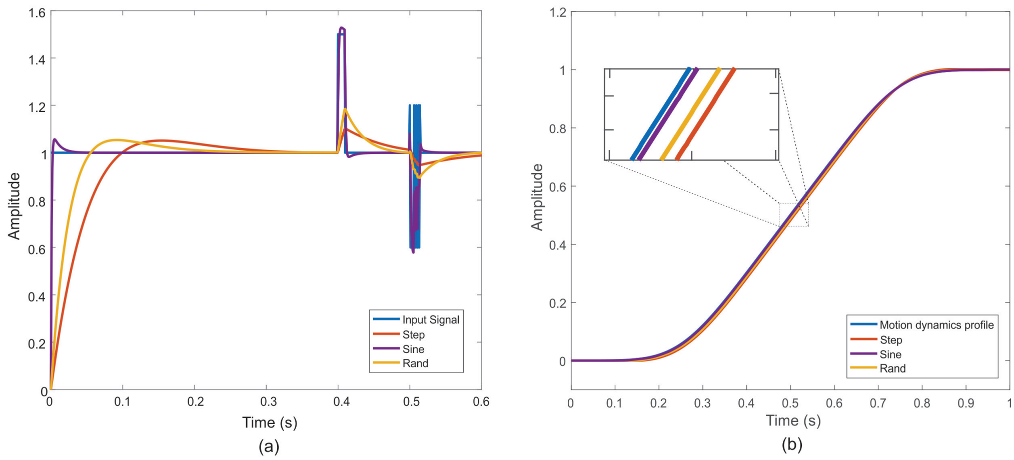

Figure 5. (**a**) System response to the step function with perturbations utilizing different controllers. (**b**) Real system response to a trajectory with a Gaussian acceleration profile, utilizing distinct controllers.

The computer evaluation was performed by introducing a stepped signal with perturbations in the closed-loop model of the system to obtain the performance indices described in Section 2, from (1) through (4), as is shown in Table 2. These performance indices are used for assessing the control system's robustness to perturbations and tracking. From these simulation results, the PID controller tuned through the sinusoidal transfer function displayed the closest behavior to that of the real system.

Table 2. Performance evaluation through the simulation of a PID controller with stepped, sinusoidal, and random signal stimuli.

	IAE	ISE	ITAE	ITSE
C_{step}	0.0558	0.0235	0.0096	0.0022
C_{sine}	0.0058	0.0016	0.0000138	0.000489
C_{rand}	0.0386	0.0139	0.0081	0.0018

3.5. Performance Evaluation on a Real System

The real system was stimulated to follow a trajectory described by a Gaussian acceleration profile, to obtain its response experimentally. Figure 5b depicts the real system behavior under the distinct PID controller tunings defined in the previous section. The observed behaviors were quite similar among them; however, a close inspection reveals differences in the trajectory tracking for each PID controller designed from the estimated TF of the system, considering the distinct input stimuli. From the performed experimentation, it is noticeable that the PID controller configuration obtained for the sinusoidal input stimulus had the best trajectory tracking in reference to the other two configurations, which was corroborated quantitatively by computing the performance indices described in Section 2, from (1) through (4), as exhibited in Table 3.

Table 3. Performance evaluation of a real system response for a PID controller with stepped, sinusoidal, and random signal stimuli.

	IAE	ISE	ITAE	ITSE
C_{step}	0.0196	0.000297	0.01846	0.000272
C_{sine}	0.0031	0.0000079	0.002818	0.000007
C_{rand}	0.0128	0.000134	0.01183	0.0001213

4. Discussion

System identification is a fundamental procedure when tuning a PID controller; however, most works, in the reviewed literature, assess their proposed system identification process by comparing it against other methods [13,14]; however, a suitable identification heavily depends on the input stimulus and the estimated TF order, as has been demonstrated in this work; if they are misappraised, the controller adjustment will take a long time and will be excessively complex and tedious. On the other hand, if the TF of the system to be controlled is available, the controller tuning will take a short time and will be simple, improving the system performance considerably. The obtained results from the exhaustive experimental analysis performed in this work demonstrated that a close approximation of the system dynamics is attained through a second-order TF, employing a sinusoidal input stimulus, since this estimation nearly mimics the dynamics of the real system providing the closest tracking of the reference signal, different from the other-order TF estimations, as depicted in Figure 4g–i. Figure 5 shows the system performance obtained through the proposed approximation, whereas Tables 2 and 3 show the integral errors computed as described in (1) through (4). In this regard, previous approaches in the literature [15–21] did not provide the parameters used for estimating the corresponding system TF (i.e., the input stimuli and the TF order), which are crucial for inferring a reliable approximation to the real system dynamics. On the other hand, it is worth noting that utilizing performance indices to assess the system identification process during the PID controller tuning allows determining the controller efficiency in tracking the reference point and the control system response to perturbations, different form previous works [23–25], where just the controller tuning process was assessed. Finally, Figure 6 shows a statistical analysis on tracking the trajectory generated from the Gaussian acceleration profile, utilizing the PID controller tunings for the estimated system TF. The examination consisted of 20 different trails for each designed controller, obtaining the corresponding performance indices (i.e., integral errors), each time. The derived results confirmed that the system inferred by considering a sinusoidal input stimulus and a second-order TF is the one that best represents the dynamics of the experimental system for which the PID controller designed from this TF performs better on tracking the reference signal; therefore, it presents the smallest errors, in addition to having the least dispersion of information among the tests carried out.

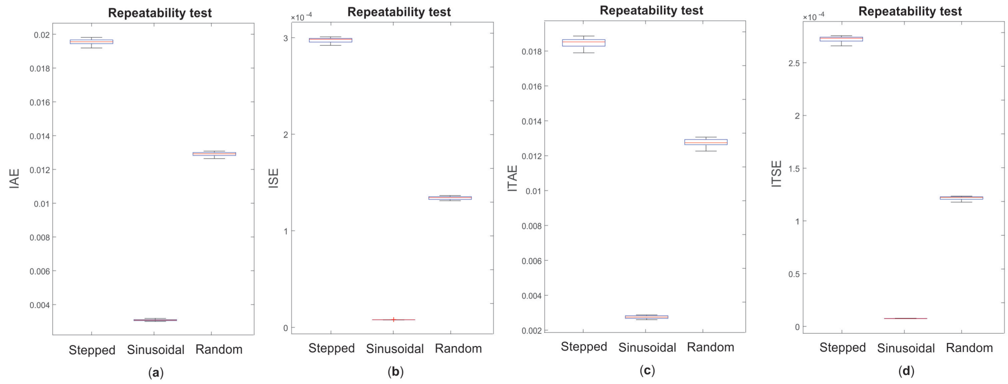

Figure 6. Repeatability tests for the three transfer functions identified through the stepped, sinusoidal, and random input stimuli, (**a**) IAE, (**b**) ISE, (**c**) ITAE, and (**d**) ITSE evaluation criteria.

5. Conclusions

System identification, which consists of building mathematical models of dynamic systems from observed input and output signals, is an important area in control theory, because whether a model is or is not appropriate for a control design depends on both the controller to be implemented and the mismatch between the plant and the model achieved through identification. Therefore, the comprehensive study in this work highlighted that the TF identification process is a critical part in the PID controller configuration because its design time and performance directly depend on how the inferred representation closely mimics that of the real system to be controlled. On the other hand, this study demonstrated the relevance for a linear control system on choosing an excitation stimulus during the identification process through the empirical method (gray-box) of the system to be controlled. From the in-depth experimentation carried out, it was observed that the sinusoidal input stimulus allowed estimating a transfer function that represents the dynamics of the system to be controlled more accurately than utilizing the stepped and random stimuli. The experimentally obtained results were validated quantitatively utilizing the performance indices the integral squared error (ISE), integral time squared error ($ITSE$), integral absolute error (IAE), and integral of time-weighted absolute value of error ($ITAE$), which are commonly used in control system design, assessing: (i) the PID controller's response to the step input, (ii) the tracking of a trajectory generated through a Gaussian acceleration profile for a link of a Cartesian robot, and (iii) the statistical repeatability of the obtained results. Hence, considering all these analyses, it can be concluded that the empirical system identification method provides a highly accurate TF for the system to be controlled by stimulating it through a sinusoidal input signal, which is validated by means of the qualitative performance indices, reaching higher precision and lower errors for large and small changes during trajectory tracking than the corresponding TF inferred utilizing stepped and random stimuli. Finally, as future work, it is desired to apply this study to more-complex control systems, as well as to evaluate other control schemes or techniques for tuning controllers based on the premise of the identification process's importance. On the other hand, an exhaustive analysis of the frequency analysis and the limitations of the robustness margins will be carried out.

Author Contributions: J.G.-V. participated in all steps of the research method's conceptualization, the materials and methods, the experimentation, the validation, the writing—original draft; C.R.-D., participated in the conceptualization, resources, supervision, and investigation; all authors participated in the writing—review and editing, visualization, and formal analysis (J.G.-V., E.G.-V., C.R.-D., E.C.-Y., L.M.L.-C. and G.H.-G.). All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

PID	Proportional–integral–derivative
TF	Transfer function
ISE	Integral squared error
ITSE	Integral time squared error
IAE	Integral absolute error
ITAE	Integral of time-weighted absolute value of error
DAS	Data acquisition system
FPGA	Field programmable gate array
RLS	Recursive least squares
LMS	Least-mean squares
KF	Kalman filter
GA	Genetic algorithm
PSO	Particle swarm optimization

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