International Journal of Electrical and Computer Engineering (IJECE)
Vol. 6, No. 1, February 2016, pp. 167~176
ISSN: 2088-8708, DOI: 10.11591/ijece.v6i1.8694

Identification of Nonlinear Systems Structured by Wiener-Hammerstein Model

A Brouri, S Slassi
ENSAM, AEEE Departm, L2MC, Moulay Ismail University, Meknes, Morocco

Article Info

Article history:

Received Jul 12, 2015
Revised Oct 25, 2015
Accepted Nov 16, 2015

Keyword:

Hard nonlinearity
Frequency system identification
Wiener models
Hammerstein models

ABSTRACT

Wiener-Hammerstein systems consist of a series connection including a nonlinear static element sandwiched with two linear subsystems. The problem of identifying Wiener-Hammerstein models is addressed in the presence of hard nonlinearity and two linear subsystems of structure entirely unknown (asymptotically stable). Furthermore, the static nonlinearity is not required to be invertible. Given the system nonparametric nature, the identification problem is presently dealt with by developing a two-stage frequency identification method, involving simple inputs.

Corresponding Author:

Adil Brouri,
Departement of AEEE,
ENSAM, L2MC, Moulay Ismail University,
ENSAM, Marjane 2, BP 4024, Meknes, Morocco.
Email: a.brouri@ensam-umi.ac.ma & brouri_adil@yahoo.fr

1. INTRODUCTION

Wiener-Hammerstein systems consist of a series connection including a nonlinear static element sandwiched with two linear subsystems (Figure 1). Accordingly, this structureof models can be viewed as a generalization of Hammerstein and Wiener models and so it is expected to feature a superior modeling capability. This has been confirmed by several practical applications e.g. paralyzed skeletal muscle dynamics [1]. Note that, the internal signals: $v(t)$, $w(t)$, $x(t)$ and $\xi(t)$ are not accessible to measurements. The only measurable signals are the system input $u(t)$ and output $y(t)$.

As a matter of fact, Wiener-Hammerstein systems are more difficult to identify than the simpler Hammerstein and Wiener models. The complexity of the former lies in the fact that these systems involve tree internal signals not accessible to measurements, whereas the latter only involve two. Then, it is not surprising that only a few methods are available that deal with Wiener-Hammerstein system identification.

The available methods have been developed following three main approaches i.e. iterative nonlinear optimization procedures e.g. [2]-[3]; stochastic methods e.g. [4]-[5]; frequency methods [6]-[9].

Roughly, the iterative methods (e.g. [2]-[3]) necessitate a large amount of data; since computation time and memory usage drastically increase, and have local convergence properties which necessitates that a fairly accurate parameter estimates are available to initialize the search process. This prior knowledge is not required in stochastic methods but these are generally relied on specific assumption on the input signals (e.g. gaussianity, persistent excitation....) and on system model (e.g. MA linear subsystems, smooth nonlinearity). The frequency methods are generally applied to nonparametric systems under minimal assumptions and only require simple periodic excitations. But, they sometime necessitate several data generation experiments.

The present identification method is quite different of previous frequency methods. In [3] the identification methods require a special design of the input signal.

In [9] the identification method is based on the best linear approximation technique using class of Gaussian (-like) signals. In [10], the authors show that there are many local minima, the estimation must to be repeated several times with different starting values to increase the chances of finding a model corresponding to a good local minimum. In [11], an approach based on the standard SVM for regression was presented. The quite poor results obtained in that work highlighted some of the limitations of the method. In particular, only a NFIR model structure was taken into account, which did not perform well since the considered system has a long impulse response. Another problem was given by the high computational time and memory usage, which made it difficult to work with a large amount of data. Several SVM-like approaches (e.g. [12]-[13]), based on the least squares SVM (LSSVM), are characterized by a very high number of parameters.

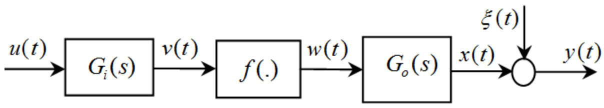

Figure 1. Wiener-Hammerstein Model structure

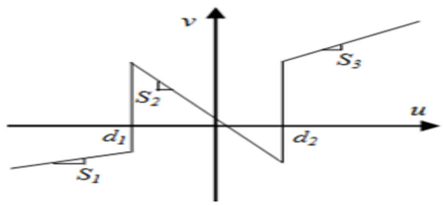

Figure 2. Hard nonlinearity with preload

In this paper, a frequency-domain identification scheme is designed for Wiener-Hammerstein systems involving two linear subsystems (asymptotically stable) of entirely unknown structure, unlike many previous works. Quite a few previous studies have dealt with block-oriented systems (of any type) that involve piecewise affine nonlinearities (Figure 2) that are, possibly discontinuous and of a priori unknown structure. The system nonlinearity can have several effects [6]. In particular, it may contain a saturation effect or dead zone. One key contribution of the present work is to show that the system identification is possible without passing by an orthogonal series expansion of the (possibly) discontinuous input nonlinearity. Given the system nonparametric nature, the identification problem is presently dealt with by developing a two-stage frequency identification method. First, the identification of system nonlinearity can be achieved by using a set of constant points. Then, the linear subsystems can be dealt by developing a frequency identification method.

The outline of the remaining part of this paper consists of 4 sections. The identification problem is formally described in Section 2. Section 3 is devoted to the identification of the system nonlinear element. The linear subsystems identification is discussed in Section 4. Simulations are presented in Section 5.

2. IDENTIFICATION PROBLEM STATEMENT

We are interested in systems that can be described by the Wiener-Hammerstein structure (Figure 1) with hard nonlinearity (Figure 2) with known segments number q. This model is analytically described by the following equations:

$$v(t)=g_i(t)*u(t) \tag{1a}$$

$$w(t) = f\left(v(t)\right) = f\left(g_i(t)*u(t)\right) \tag{1b}$$

$$y(t) = g_o(t) * w(t) + \xi(t) = g_o(t) * f\left(v(t)\right) + \xi(t) \tag{1c}$$

where $g_i(t)=L^{-1}(G_i(s))$ and $g_o(t)=L^{-1}(G_o(s))$ are the inverse Laplace transform of $G_i(s)$ and $G_o(s)$ (respectively); *refers to the convolution operation. The linear subsystems are of entirely unknown structure. There are only

supposed to be asymptotically stable (because system identification is carried out in open loop) and with nonzero static gain (i.e. $G_i(0) \neq 0$ and $G_o(0) \neq 0$). Also, note that the nonzero static-gain requirement is satisfied by most real life systems. In fact, only derivative systems make an exception that can be coped with using ad-hoc adaptations of the method developed in this paper.
For a problem of identifiability, at least one of nonlinearity segment has nonzero slope. The external noise $\xi(t)$ is supposed to be a zero-mean stationary sequence of independent random variables and ergodic.

Let $[u_m \quad u_M]$ be the working interval. The problem complexity also lies in the fact that the internal signals are not uniquely defined from an input-output viewpoint. In effect, if $(G_i(s), f(v), G_o(s))$ is representative of the system then, any model of the form $(G_i(s)/k_1\ ,\ k_2 f(k_1 v)\ ,\ G_o(s)/k_2)$ is also representative whatever the real numbers $k_1 \neq 0$ and $k_2 \neq 0$ (Figure 3). To get benefit of model plurality, these constants can be chosen as follows: $k_2 = G_o(0)$ and $k_1 = G_i(0)$.
Accordingly, the system to be identified is described by the transfer functions:

$$\bar{G}_i(s) = G_i(s) / G_i(0)\ ; \quad \bar{G}_o(s) = G_o(s) / G_o(0) \tag{2a}$$

and the nonlinearity:

$$\bar{f}(x) = G_o(0) f\left(G_i(0) x\right) \tag{2b}$$

Then, the focus model is characterized by the following properties:

$$G_i(0) = G_o(0) = 1 \tag{3}$$

Equation (3) implies that, if $u(t)$ is constant then the steady-state undisturbed output $x(t)$ depends only on the input value and the nonlinearity $f(.)$. Specifically, let:

$$u(t) = U \ \text{ for } \ t \in [0 \quad kT_r], \ \text{ with } \ k>1 \tag{4}$$

where k is any integer and T_r is comparable to the system rise time. Then, the internal signal $x(t)$, in the steady-state, is of the form of:

$$x(t) = f(U) \tag{5}$$

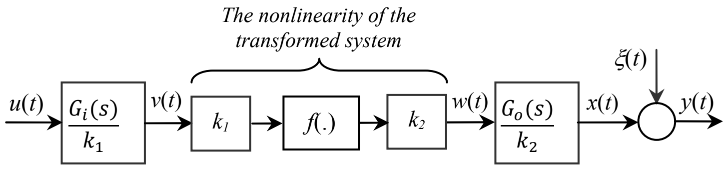

Figure 3. Wiener-Hammerstein Model multiplicity

3. IDENTIFICATION OF SYSTEM NONLINEARITY

The Wiener-Hammerstein system is excited by a set of constant inputs $u(t) \in \{U_1; \ldots ; U_N\}$, where the number N is arbitrarily chosen by the user and $U_1 < U_2 < \ldots < U_N$. Afterward, using the fact that $y(t) = x(t) + \xi(t)$, it is readily obtained from (5) that, the steady state of the system output $y(t)$ can be expressed as follows:

$$y(t) = f(U_j) + \xi(t) \quad \text{where } j \in \{1; \ldots ; N\} \tag{6}$$

Hence, the estimate of $f(U_j)$, for any input U_j, can be recovered by averaging $y(t)$ on a sufficiently large interval (the noise $\xi(t)$ is zero-mean). The above results suggest the following estimator for $f(.)$:

$$\hat{f}(U_j) = \hat{X}_j(k) = \frac{1}{kT_r}\int_0^{kT_r} y(t)\,dt \tag{7}$$

with $j = 1 \ldots N$. Accordingly, a number of points of the nonlinear function $f(.)$ can thus be accurately estimated (i.e. the resulting system, in the steady state, boils down to the linearity part $f(.)$). This yields the following statement:

Proposition 1

The couple of points $\left(U_j\ ,\ \hat{X}_j(k)\right)$, for $j = 1 \ldots N$, determined in the Nonlinearity Estimator, converge (in probability) to the trajectory of $f(.)$.

Accordingly, from (7), one gets estimates of N points $\left(U_j, f(U_j)\right)$ belonging to $f(.)$. Furthermore, the larger the parameter N is, the better estimation accuracy. Then, by successively connecting all available points $\left\{(U_j, f(U_j)); k = 1 \cdots N\right\}$, a piecewise affine approximation of $f(.)$ is obtained. If the number of obtained segment is less than q, the nonlinear system is excited by other constant inputs. Finally, let choose any segment l of the identified nonlinearity with nonzero slope.

4. LINEAR SUBSYSTEMS IDENTIFICATION

In this section, an identification method is proposed to obtain estimates of the complex gain corresponding to the two linear subsystems $G_i(j\omega)$ and $G_o(j\omega)$ for a set of frequencies $\left\{\omega_1; \ldots; \omega_m\right\}$. Let $\varphi_i(\omega) = \arg\left(G_i(j\omega)\right)$ and $\varphi_o(\omega) = \arg\left(G_o(j\omega)\right)$. For simplicity, we presently suppose that the nonlinearity identification have been exactly determined. Then, let define the variables (for any ω):

$$\varphi(\omega) = \varphi_i(\omega) + \varphi_o(\omega) \tag{8a}$$

$$\left|G(j\omega)\right| = \left|G_i(j\omega)\right|\left|G_o(j\omega)\right| \tag{8b}$$

The subsystem identification can be implemented in two stages:
Firstly, an accurate estimates of $\left|G(j\omega_k)\right|$ and $\varphi(\omega_k)$, for any frequency $\omega_k \in \left\{\omega_1; \ldots; \omega_m\right\}$, can be determined.

The identification problem under study is dealt using a method based on the frequency approach. The Wiener-Hammerstein systemis excited with a given sine input:

$$u(t) = u_o + U\sin(\omega_k t) \tag{9}$$

where the amplitude $U > 0$ is a priori small value. The choice of u_o can be performed using the experimental data of nonlinearity estimation. It can take any value in the vicinity from the center of segment l. Then, as the linear subsystem $G_i(s)$ is asymptotically stable, it follows from (3)-(9), one has in the steady state:

$$v(t) = u_o + U\left|G_i(j\omega_k)\right|\sin(\omega_k t + \varphi_i(\omega_k)) \tag{10}$$

If $v(t)$ spans only the chosen segment, one gets:

$$w(t) = S^{*}v(t) + P^{*} \tag{11}$$

where S^* is the slope of segment l and P^* is the value of $w(t)$ when $v(t)=0$. In practice, this case can be easily detected by a simple inspection of the output signal. For a small value of the amplitude U, the steady state of system output $y(t)$ is a sine signal (up to noise). As soon as, $v(t)$ spans at least two segments, $y(t)$ is not a sine signal. Accordingly, a judicious choice for U can be given practically. Then, from (10)-(11), the internal signal $w(t)$ is written in the following form:

$$w(t) = US^* \left|G_i(j\omega_k)\right| \sin(\omega_k t + \varphi_i(\omega_k)) + S^* u_o + P^* \tag{12}$$

As the linear subsystem $G_o(s)$ is asymptotically stable, it follows from (12) and (8a-b) that, the steady state undisturbed output $x(t)$ can be expressed as follows:

$$x(t) = S^* u_o + P^* + US^* \left|G(j\omega_k)\right| \sin\left(\omega_k t + \varphi(\omega_k)\right) \tag{13}$$

Finally, as $y(t) = x(t) + \xi(t)$, one immediately gets:

$$y(t) = US^* \left|G(j\omega_k)\right| \sin\left(\omega_k t + \varphi(\omega_k)\right) + y_o + \xi(t) \tag{14}$$

where:

$$y_o = S^* u_o + P^* \tag{15}$$

On the other hand, recall that sine signals that oscillate at the same frequency as $\sin\left(\omega_k t + \varphi(\omega_k)\right)$ and having the amplitude U are of the form:

$$z_\delta(t) = U \sin\left(\omega_k t + \delta\right) \tag{16}$$

where $\delta \in IR$ is arbitrary and IR denotes the set of real numbers. It is readily seen that:

$$U \sin\left(\omega_k t + \varphi(\omega_k)\right) = z_{\varphi(\omega_k)}(t) \tag{17}$$

Let $C_\delta^{\omega_k,U,u_o}$ is the parameterized locus constituted of all points of coordinates $\left(z_\delta(t), x(t)\right)$. These curves are viewed as a generalization of the Lissajous curves used in linear system frequency analysis [5].
These ideas are formalized in the following proposition:

Proposition 2

Consider the Wiener-Hammerstein system described by equations (1a-c) and excited by the input (9), with u_0 and U are judiciously chosen so that the system output $y(t)$ is sine signal (up to noise). Then, one has:
The locus $C_\delta^{\omega_k,U,u_o}$ is a linear curve if and only if $\delta = \varphi(\omega_k)$ (modulo π).

Another key idea of the proposed approach (getting benefit from Proposition 2) is to determine the gain modulus $\left|G(j\omega_k)\right| = \left|G_i(j\omega_k)\right|\left|G_o(j\omega_k)\right|$ and the phase $\varphi(\omega_k) = \varphi_i(\omega_k) + \varphi_o(\omega_k)$ by tuning the parameter δ until the locus $C_\delta^{\omega_k,U,u_o}$ shows linear curve. The point is that the locus $C_\delta^{\omega_k,U,u_o}$ depends on the signal $x(t)$ which is not accessible to measurement. This is presently coped with making full use of the information at hand, namely the periodicity (with period $2\pi/\omega_k$) of both $z_\delta(t)$ and $x(t)$ and the ergodicity of the noise $\xi(t)$. Bearing these in mind, the relation $y(t) = x(t) + \xi(t)$ suggests the following estimator:

$$\hat{x}(t, M) = \frac{1}{M} \sum_{j=1}^{M} y(t + jT_k)\,; \quad t \in [0, T_k) \tag{18a}$$

$$\hat{x}(t + jT_k, M) = \hat{x}(t, M) \quad \text{for any integer } j > 0 \tag{18b}$$

where $T_k = 2\pi / \omega_k$ and M is a sufficiently large integer. Specifically, for a fixed time instant t, the quantity $\hat{x}(t,M)$ turns out to be the mean value of the (measured) sequence $\{y(t+jT_k);\, j=0\ 1\ ...\}$. Then, an estimate $\hat{C}_{\delta,M}^{\omega_k,U,u_o}$ of $C_{\delta}^{\omega_k,U,u_o}$ is simply obtained substituting $\hat{x}(t,M)$ to $x(t)$ when constructing $C_{\delta}^{\omega_k,U,u_o}$. These remarks lead to the following proposition:

Proposition 3

Consider the problem statement of Proposition2. Then, one has:

1) $\hat{x}(t,M)$ converges in probability to $x(t)$ (as $M \to \infty$).

2) $\hat{C}_{\delta,M}^{\omega_k,U,u_o}$ converges in probability to $C_{\delta}^{\omega_k,U,u_o}$ (as $M \to \infty$).

On the other hand, let δ^* the corresponding value of δ and $s(\omega_k)$ the slop of the obtained curve $C_{\delta^*}^{\omega_k,U,u_o}$. Knowing the sign of S^*, the phase $\varphi(\omega_k)$ can be recovered modulo 2π. Let us consider the parameter γ defined as follows:

$$\gamma = 0 \ \text{ if } \operatorname{sign}(S^*) = \operatorname{sign}\left(s(\omega_k)\right) \text{ else } \gamma = 1 \tag{19}$$

Let $\hat{s}_M(\omega_k)$ denotes the estimate of $s(\omega_k)$. Then, an estimate $\left(\hat{\varphi}_M(\omega_k), \left|\hat{G}_M(j\omega_k)\right|\right)$ of $\left(\varphi(\omega_k), \left|G(j\omega_k)\right|\right)$ can be determined, one has thus, for any frequency ω_k :

$$\hat{\varphi}_M(\omega_k) = \hat{\varphi}_i(\omega_k, M) + \hat{\varphi}_o(\omega_k, M) = \delta^* + \gamma\pi \ \ (\text{modulo}\pi) \tag{20a}$$

$$\left|\hat{G}_M(j\omega_k)\right| = \left|\hat{G}_i(j\omega_k, M)\right| \left|\hat{G}_o(j\omega_k, M)\right| = \left|\frac{\hat{s}_M(\omega_k)}{S^*}\right| \tag{20b}$$

5. SIMULATION

The identification method described in this paper will now beillustrated by simulation using Matlab/Simulink. Presently, the system is characterized by:

$$G_i(s) = \frac{0.2}{(s+1)(s+0.2)} \ \text{ and } \ G_o(s) = \frac{0.05}{(s+0.1)(s+0.5)} \tag{21}$$

The considered nonlinear elementis illustrated by Figure 4. The noise $\xi(t)$ is a sequence of normally distributed (pseudo) random numbers, with zero-mean and standard deviation $\sigma_\xi = 0.02$. Firstly, the aim is to estimate the system nonlinearity. The identification method described in Section 3 will now be applied and, accordingly, the system is successively excited by $N = 11$ constant inputs $\left\{U_j;\, j = 1 \ldots N\right\}$, where the values U_j and the obtained estimates of $f(U_j)$ are shown in Figure 5. The true nonlinearity and the set of points $\left(U_j\ , \hat{f}_L(U_j)\right)$ $(j = 1 \ldots 11)$, are represented in Figure 6. By connecting the set of collinear points (Figure 6). The $q = 3$ segments are then obtained.

The nonlinear system is excited by (9). Figure 7 shows example of obtained results when $v(t)$ spans at least two segments. Then, $y(t)$ is not a sine signal. This confirms the result already obtained using the plot $\hat{C}_{\delta,M}^{\omega_k,U,u_o}$. This latter, turns out to be a non static curve, whatever $\delta \in [0\ \ 2\pi)$ (Figure 9a-b). For a small value of U, e.g. $U = 0.25$, $\omega_1 = 0.01\,(rd / s)$ and $u_o = -0.75$, Figure 9a shows the measured output $y(t)$. This signal turns out to be a sine signal (up to noise). Then, using the estimator (18a-b), the filtered output $\hat{x}(t,M)$ is generated. $\hat{x}(t,M)$ is represented in (Figure 9b). The locus $\hat{C}_{\delta,M}^{\omega_1,U,u_o}$ is plotted for different $\delta \in \left[0 \quad 2\pi\right)$ and a sample of the obtained curves is shown by Figures 10a-b. It is seen that $\hat{C}_{\delta,M}^{\omega_1,U,u_o}$ associated to $\delta = 2$ is not linear ($\delta \neq \varphi(\omega_k)$). Further, the curve $\hat{C}_{\delta,M}^{\omega_1,U,u_o}$ associated to $\delta^* = 3.01$ is affine portion. Additionally, it is seen that the sign of S^* is different from that of $\hat{C}_{\delta,M}^{\omega_1,U,u_o}$. We have thus shown that $\hat{\varphi}_M(\omega_1) = \delta^* + \pi = 6.15\,(rd)$ (modulo 2π). From Figure 10b, one has $\hat{s}_M(\omega_k) = 0.97$.

The estimator (20b) is used to get estimates of the modulus $|G(j\omega_k)|$. Accordingly, $|\hat{G}_M(j\omega_k)| \approx 0.97$. Other results show in Table 1.

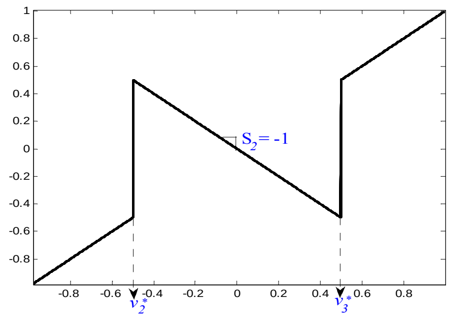

Figure 4. Nonlinear hard element *f*(.) considered in simulation

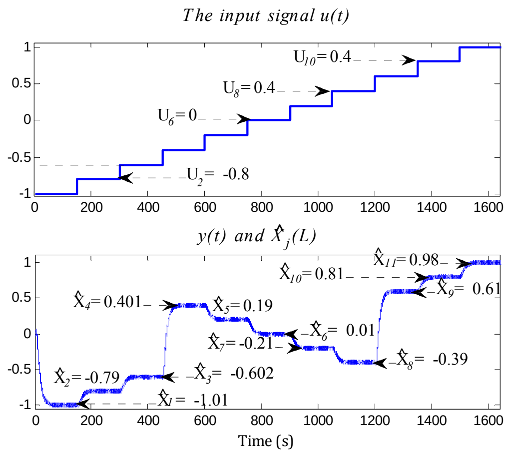

Figure 5. $u(t)$, $y(t)$ and the undisturbed output estimate

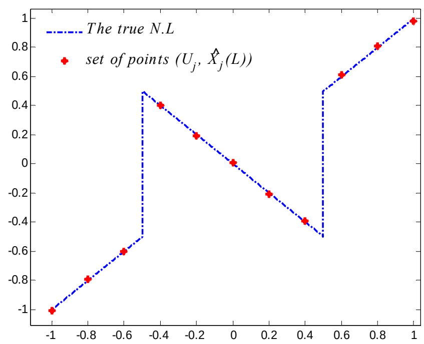

Figure 6. The true N.L and set of estimated points

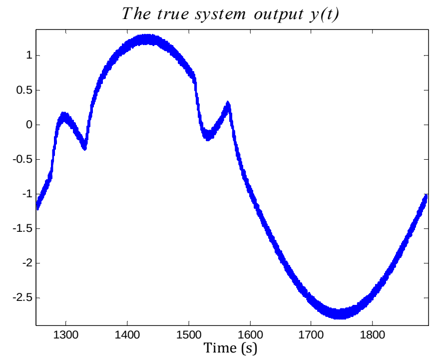

Figure 7. The steady-state output $y(t)$ obtained over one period

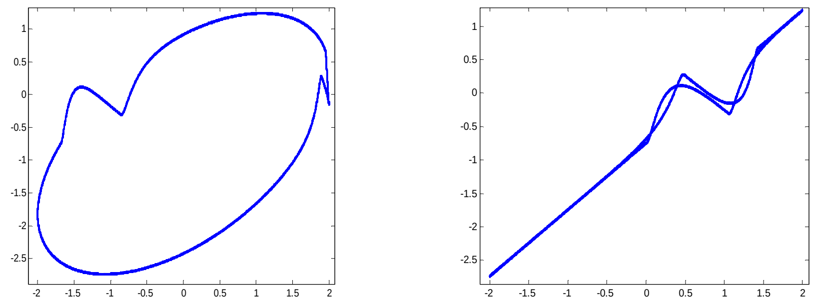

Figure 8. a. The locus $\hat{C}_{\delta,M}^{\omega_1,U,u_o}$ for $\delta = 5.1 \neq \varphi(\omega_k)$; b. $\hat{C}_{\delta,M}^{\omega_1,U,u_o}$ for $\delta = 6.1 = \varphi(\omega_k)$

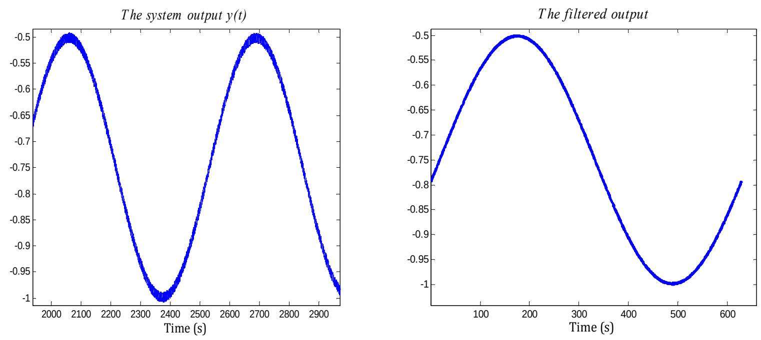

Figure 9. a. The steady-state of $y(t)$; b. One period of $\hat{x}(t, M)$

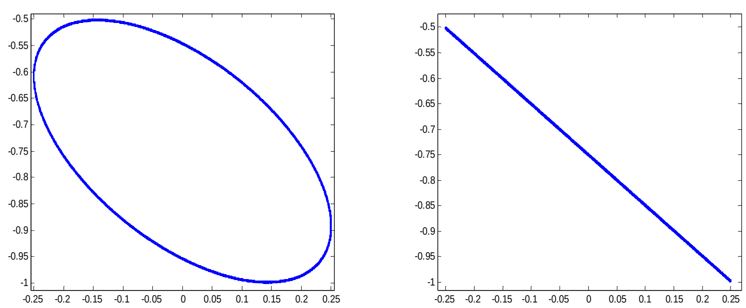

Figure 10. a. $\hat{C}_{\delta,M}^{\omega_1,U,u_o}$ for $\delta = 2\,(rd)$; b. $\hat{C}_{\delta,M}^{\omega_1,U,u_o}$ for $\delta = 3.01\,(rd)$

Table 1. Frequency gain estimates

Frequency gain estimates $\hat{G}_M(j\omega_k)$			
ω_k (rd/s)	0.01	0.05	0.1
$\varphi(\omega_k)$ (rd)	6.1	5.42	4.74
$\hat{\varphi}_M(\omega_k)$ (rd)	6.15	5.38	4.78
$\lvert G(j\omega_k)\rvert$	0.99	0.86	0.62
$\lvert\hat{G}_M(j\omega_k)\rvert$	0.97	0.88	0.65

6. CONCLUSION

We have developed a new frequency identification method to deal with Wiener-Hammerstein systems; the identification problem is addressed in presence of hard nonlinearity and two linear subsystems of structure entirely unknown. The present study constitutes a significant progressin frequency-domain identification of block-oriented nonlinear system identification. The originality of the present study lies in the fact that the system is not necessarily parametric and of structure totally unknown. Another feature of the method is the fact that the exciting signals are easily generated and the estimation algorithms can be simply implemented. Then, the complex gains (modulus gains and phases) of linear subsystems can be obtained.

REFERENCES

[1] Bai EW, Cai Z, Dudley-Javorosk S and Shields RK. Identification of a modified Wiener-Hammerstein system and its application in electrically stimulated paralyzed skeletal muscle modeling. *Automat. Contr*. 2009; 45(3): 736-743.

[2] Marconato A, Sjoberg J and Schoukens J. Initialization of nonlinear state-space models applied to the Wiener-Hammerstein benchmark. *Control Engineering Practice*. 2012; vol. 20: 1126-1132.

[3] Crama P, Schoukens J. Computing an initial estimate of a Wiener-Hammerstein system with a random phase multisine excitation. *IEEE Transactions on Instrumentation and Measurement*. 2005; vol. 54: 117-122.

[4] Pillonetto G, Chiuso A and Nicolao GD. Prediction error identification of linear systems: a nonparametric Gaussian regression approach. *Automatica*. 2011; 47(2): 291-305.

[5] Bershad NJ, Celka P, McLaughlin S. Analysis of stochastic gradient identification of Wiener-Hammerstein systems for nonlinearities with Hermite polynomial expansions. *IEEE Trans*. Signal Process. 2001; vol. 49: 1060-1071.

[6] Brouri A, Giri F, Chaoui FZ and Amdouri A. *Frequency Identification of Hammerstein-Wiener Systems with Piecewise Affine Input Nonlinearity*. 19th IFAC, World Congress. Cape Town. 2014; 10030-10035.

[7] Brouri A. *Frequency Identification of Wiener-Hammerstein Systems*. SIAM Control &Its Applications. Paris, France. 2015.

[8] Giri F, Rochdi Y, Radouane A, Brouri A, Chaoui FZ. Frequency Identification of nonparametric Wiener systems containing backlash nonlinearities. *Automatica*. 2013; vol. 49: 124-137.

[9] Paduart J, Lauwers L, Pintelon R, Schoukens J. Identification of a Wiener–Hammerstein system using the polynomial nonlinear state space approach. *Control Engineering Practice*. 2012; vol. 20: 1133-1139.

[10] Wills A, Ninness B. *Estimation of generalised Wiener-Hammerstein systems*. 15th IFAC symposium on system identification. Saint-Malo, France. 2009; 1104-1109.

[11] Marconato A, Schoukens J. *Identification of Wiener-Hammerstein benchmark data by means of support vector machines*. 15th IFAC symposium on system identification. Saint-Malo, France. 2009.

[12] Falck T, Pelckmans K, Suykens J, Moor BD. *Identification of Wiener-Hammerstein systems using LS-SVMs*. 15th IFAC symposium on system identification. Saint-Malo, France. 2009.

[13] Suykens J, Van Gestel T, De Brabanter J, De Moor B, Van dewalle J. Least squares support vector machines. Singapore: World Scientific. 2002.

[14] Weisstein EW, "Lissajous Curve" MathWorld, a Wolfram Web Resource. http://mathworld.wolfram.com/LissajousCurve.html

BIOGRAPHIES OF AUTHORS

Adil Brouri In 2000, he obtained the Agrégation of Electrical Engineering from the ENSET, Rabat, Morocco and, in 2012, he obtained a Ph.D. in Automatic Control from the University of Mohammed 5, Morocco. He has been Professeur-Agrégé for several years. Since 2013 he joined the ENSAM, University of My Ismail in Meknes, Morocco and a member of the L2MC Lab. His research interests include nonlinear system identification and nonlinear control. He published several papers on these topics.
E-mail: a.brouri@ensam-umi.ac.ma & brouri_adil@yahoo.fr

Sm Slassi Teacher at high school. His research interests include nonlinear system identification and nonlinear control.