24th COBEM - 2017

24th ABCM International Congress of Mechanical Engineering
December 3-8, 2017, Curitiba, PR, Brazil

COBEM-2017-1442
IDENTIFICATION OF STABILIZATION PARAMETERS OF REGIONAL AMAZONIAN BOATS

Flávio José Aguiar Soares
Álvaro de Azevero Peres Neto
Instituto Federal de Educação, Ciência e Tecnologia do Amazonas IFAM-CMDI, Av. Danilo Aerosa N 1672
flaviosoares@ifam.edu.br
alvaro.peres15@hotmail.com

Cleonor Crescêncio das Neves
Instituto Federal de Educação, Ciência e Tecnologia do Amazonas IFAM-CMDI, Av. Danilo Aerosa N 1672
cleonor@ifam.edu.br

Abstract. *The goal of this article is to identify parametric models for the study of vessels stability in the amazon region. The transverse stabilization of vessels aims to raise the security and comfort vessels. However, active stabilization devices are sophisticated and expensive, which practically prevent its use on amazon vessels. The literature presents models in reduced scale using passive, low cost stabilization devices. This option is limited since real boats alter the mass distribution, inertia and fundamental frequency with variable loads flux on board at any harbor, which characterizes it as a variable mass system. This proposal compares identification models of ARX, ARMAX and N4SID models applied to dynamic tests to estimate the fundamental frequency of a model boat. Knowing the fundamental frequency of the prototype boat allows us to develop easy building low cost, passive-adaptive stabilization model. The ARMAX model got the best identification results, with less medium error between the identified model, the measured signal and best approximation to the fundamental frequency. The results of simulations and analysis of the identified models are presented.*

Keywords:*ARX, ARMAX, N4SID, transverse stability, identification of the natural frequency…*

1. INTRODUCTION

The study of transverse stability seeks to raise the security and comfort at navigation. However, active stabilization devices are sophisticated and expensive, therefore not appropriate to region's economic reality. Rylo, et al (2016) study used a prototype in a physical model with the characteristics of a regional Amazonian boat. This boat was made in reduced scale 1:25 with a low cost passive stabilization device, a tank U, tuned to the same fundamental frequency of the boat model through the Lloyd model, according to equations presented in Gawad, et al (1999). Dynamic tests were performed at a University of São Paulo test tank and the results for the Response Amplitude Operator were compatible with technical papers.

However this solution is limited because it's a passive device, synchronized to only one frequency. Real boats are mass-variable systems. The flux of people and cargo between harbors change the inertia and the fundamental frequency of the vessel. The objective of this work is to use identification models to infer the natural frequency of the boat using the transverse oscillation signal and a controlled excitation signal.

We compared identification models of ARX, ARMAX and N4SID applying it to the dynamic tests signals to estimate the fundamental frequency of the boat, which was known before, W_n=1,15Hz. Therefore, it was possible to evaluate the identification algorithms. The data used in the identification was obtained in Rylo, et al (2016), with the prototype boat being excited in a test tank by train waves generated by a spectrum of frequencies from 0,8 to 1,35Hz raising it each 0,05Hz. In these tests the boat was placed perpendicularly to the impact of the waves. Boat's amplitude of the transverse oscillation was considered as output signal and the excitement wave as input signal.

2. COMPUTATIONAL PROCEDURE

We used the stochastic identification through parametric methods of the gray box type in which the ARX, ARMAX an N4SID are used with theoretical concepts presented in Aguirre (2007), Coelho and Coelho (2004), Ljung (1999), Van Overschee and De Moor (1996), and Ricco (2012). Matlab's System Identification Toolbox library functions were used. The system was considered causal in this analysis just because the boat output signal isn't anticipative and the present amplitude of the transverse oscillation depended only on the past transverse oscillation signal. The stochastic identification Backward Innovation Model problem given *b* measurements of the output $\varphi_k \in R^l$ generated by the stochastic system of order *n* given by the Equations (1), (2) and (3), as in Van Overschee and De Moor (1996). Where φ_k is the transverse oscillation of the prototype boat.

The ARX and ARMAX models follow known algorithms for parameter estimation according to the linear model represented in Equations (4), (5) and (6). Where $y(t)$ is the output, $u(td)$ is the input with a transport delay d, a integer value that is multiple of the sampling period, $H(z^{-1})$ and $G(z^{-1})$ are the transfer functions of process and transfer functions of noise, as shown in Coelho and Coelho (2004).

$$z^b_{k-1} = A^T z^b_k w^b_k \tag{1}$$

$$y_k = G^T z^b_k v^b_k \tag{2}$$

$$E = \left[\begin{pmatrix} w^b_p \\ v^b_p \end{pmatrix} \left((w^b_q)^T \ (v^b_q)^T \right) \right] = \begin{pmatrix} Q^b & S^b \\ (S^b)^T & R^b \end{pmatrix} \delta_{pq} \tag{3}$$

$$y(t) = H(z^{-1})u(t-d) + G(z^{-1})v(t) \tag{4}$$

$$H(z^{-1}) = \frac{B(z^{-1})}{F(z^{-1})A(z^{-1})} \tag{5}$$

$$G(z^{-1}) = \frac{C(z^{-1})}{D(z^{-1})A(z^{-1})} \tag{6}$$

The subspace identification methods, especially the N4SID, have characteristics that differentiates them from the ARX and ARMAX models, the state matrix $x(k)$, and follow the model shown in Equations (7), (8) e (9). Where $y(k) \in R \in$ is the output, $u(k-d) \in R^m$ is the input with a transport delay *d*, the parametric matrices $A(z^{-1}) \in R^{nxn}$, $B(z^{-1}) \in R^{nxm}$, $C(z^{-1}) \in R^{lxn}$ and $D(z^{-1}) \in R^{lxm}$ are described as dynamic matrix of the system, input matrix , output matrix, direct transmission matrix, respectively, e $x(k) \in R^n$ is the state matrix as shown in Van Overschee and De Moor(1996) and in Ricco(2012).

Moreover, the vectors $v(k) \in R^l$ and $w(k) \in R^n$ are the deterministic input and the stochastic input, and the System must obey the conditions of Equation (7) assuming that matrices $A(z^{-1})$ and $C(z^{-1})$ are observable and that the dynamic modes of the System can be excited by both the deterministic input and the stochastic input respecting the orthogonality condition of equation (3) becomes (10), with K being described as a disturbance matrix, assuming a white, stationary, uncorrelated noise and zero-noise.

$$x(k+1) = Ax(k) + Bu(k-d) + w(k) \tag{7}$$

$$y(k) = Cx(k) + Du(k-d) + v(k) \tag{8}$$

$$w(k) = Kv(k) \tag{9}$$

$$E = \left[\begin{pmatrix} w^b_p \\ v^b_p \end{pmatrix} \left((w^b_q)^T \ (v^b_q)^T \right) \right] = 0_{(n+m)x(n+l)} \tag{10}$$

Figure 1 shows the wave amplitude of input signal that excites the prototype boat at 1.15 Hz and transverse angle variation of output signal that could destabilize the boat.

Figure 2 shows the wave amplitude of input signal that excites the prototype boat at 0.9 Hz and respective output signal.

Figure 3 shows the FFT of two excitation signals, the transverse angular oscillation motion and the heave motion of the boat at 1.15Hz. In it we can see that the excitation signal is not influenced by disturbances.

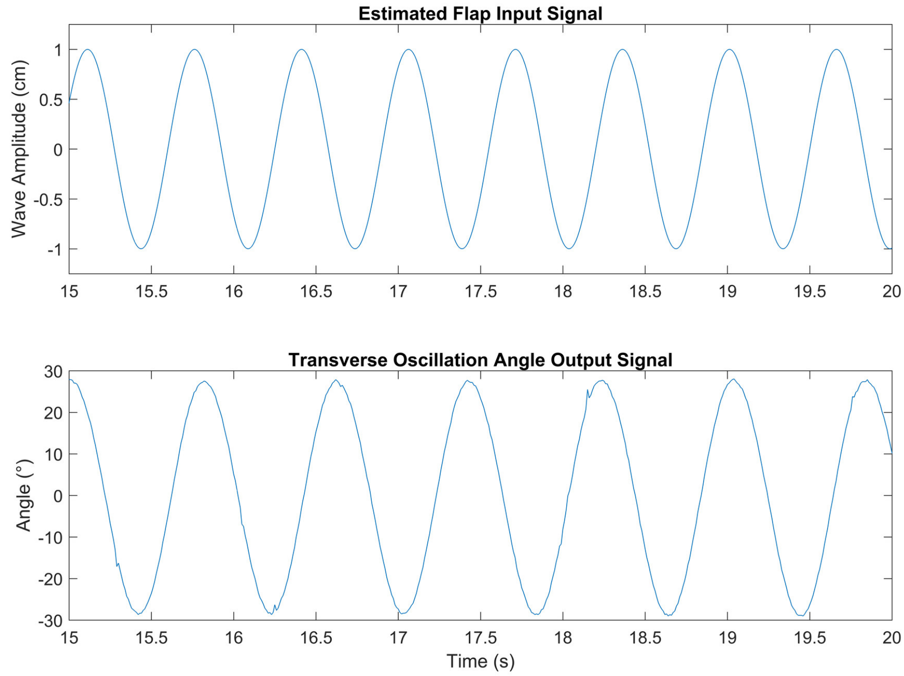

Figure 1. Input and output signal over the prototype boat at 1.15 Hz

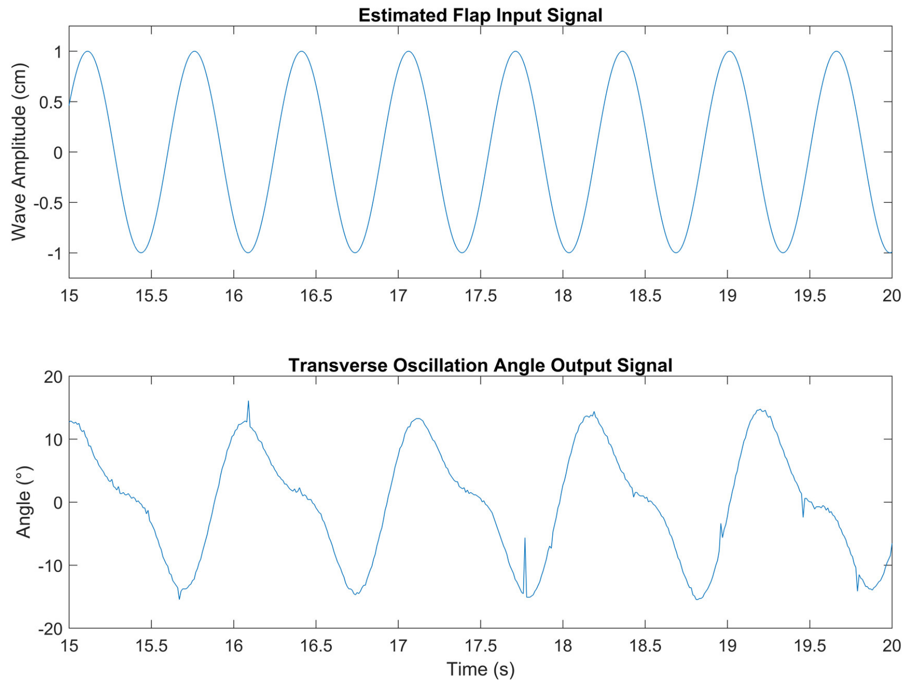

Figure 2. Input and output signal over the prototype boat at 0.9 Hz

From the Hankel singular value graph, drawn from Matlab's System Identification Toolbox, it was possible to estimate the order of the models so that there were fewer number of iterations and greater accuracy, Kitamoto and Yamaguchi (2008). This allowed us to determine that the model should be of third order and with that, the sizes of each parametric matrix of the ARX, ARMAX and N4SID. Therefore, from the algorithm Canonical Variate Algorithm (CVA) shown in

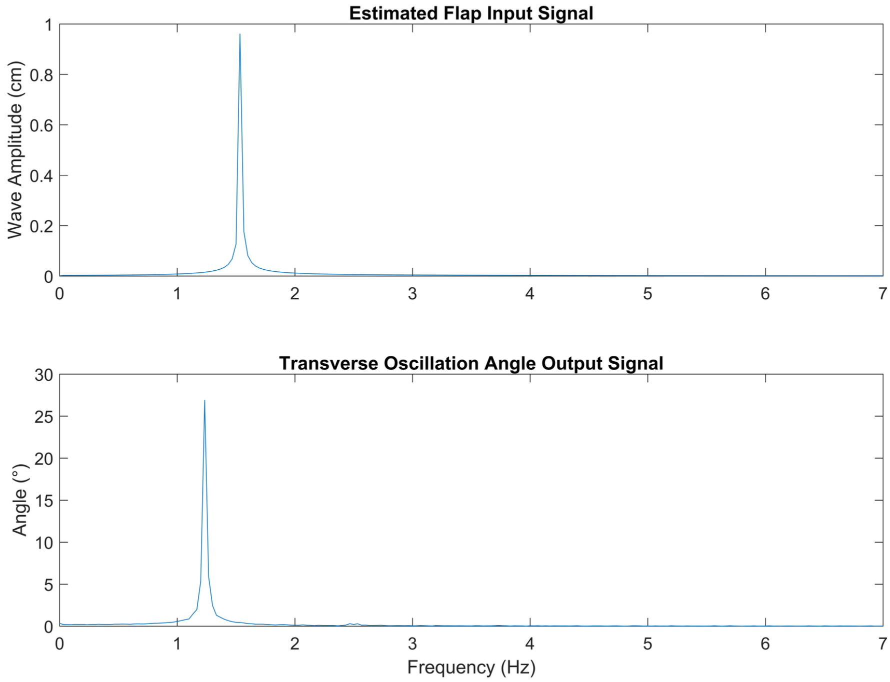

Figure 3. Respective FFT response of input and output signal over the prototype boat at 1.15 Hz

VanOverschee and De Moor (1996), Ljung (1999) and Van Overschee and De Moor (1993) it was possible to estimate the system dynamics of input, output, direct and of disturbance for the N4SID model and the ARX and ARMAX model polynomials

3. RESULTS AND DISCUSSION

Table 1 shows the dynamic polynomials and matrices' data obtained by the identification models. Value matrix $D(z^{-1})$ to N4SID model was full.

Table 1. Dynamic matrices of the identifications models' representation process.

Model	$A(z^{-1})$	$B(z^{-1})$	$C(z^{-1})$	$K(z^{-1})$
ARX	$1 - 2.955z^{-1} + 2.917z^{-2} - 0,9618z^{-3}$	$-0.00013z^{-3}$	-	-
ARMAX	$1 - 2,952z^{-1} + 2,91z^{-2} - 0.9582z^{-3}$	$-0.0001z^{-3}$	$1 + 2,98z^{-1} + 2,9789z^{-2} + 0,989z^{-3}$	-
N4SID	$0.9971 \quad -0.078 \quad -0.0001$ $0.077 \quad 0.997 \quad 0.0072$ $0.0008 \quad -0.0063 \quad 0.8529$	0.010 0.020 -0.5821	$1093 \quad -32.55 \quad -0.09$	0.0015 -0.016 -0.7327

Figure 4 shows comparative model identification to 1.15 Hz at a specific data window. ARMAX presents the best approximation results. In it we can see that the ARX model is delayed in relation to the others.

Figure 5 shows the average error between models and experimental data of each model. The best approximation point, ARMAX is in 0.90Hz, where the average error is 0.117%.

Figure 6 indicates the average model error at 1.15HZ within a specific data window. ARMAX presents the best approximated results, with a more stable and flat curve.

Figure 7 represents a percentage scale of models' errors. ARMAX presents the best approximation results.

Table 2 shows the variance error and average error of each frequency evaluated. In it, it can be observed that the ARMAX model presents the closest approximation for a tank frequency of 1.30Hz

Figure 8 indicates the model percentage error distribution on natural frequencies. ARMAX presents the best approximation results for almost all points evaluated. At 1.30Hz, ARMAX finds W_n=1.14Hz, when the prototype boat has W_n=1.15Hz.

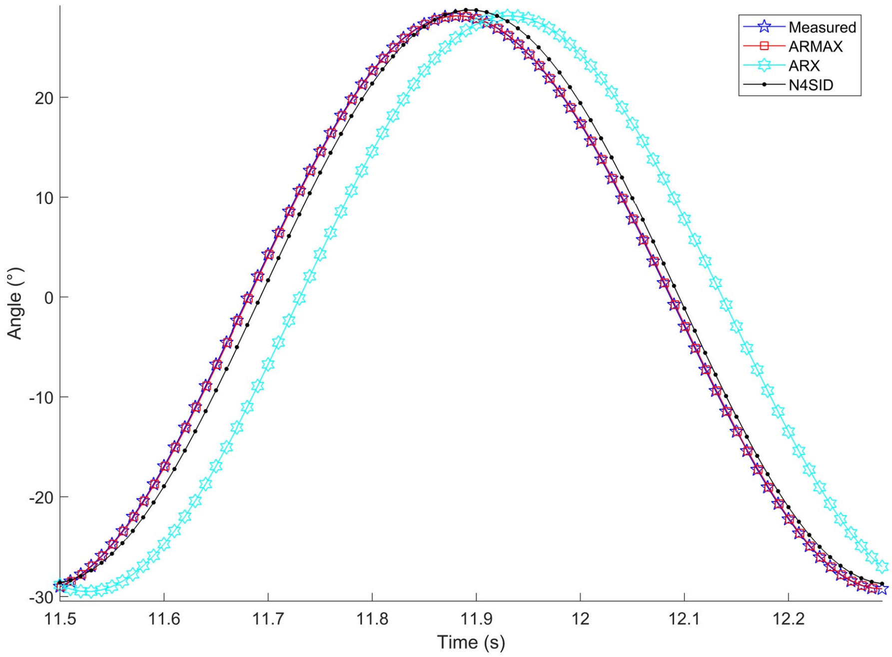

Figure 4. Model identification fidelity at 1.15Hz

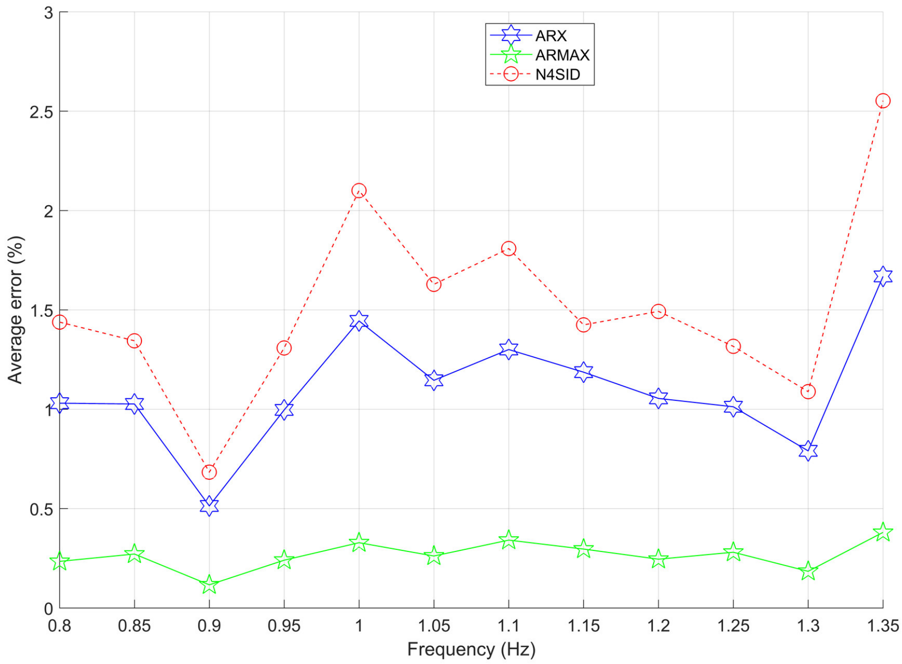

Figure 5. Model average error distribution over frequency band tests

Table 3 indicates the average error of natural frequencies of each model estimate through the damp function of the Matlab system Identification Toolbox. The ARMAX model achieved the best results, with the lowest global average error of 0.2657%. The natural frequency that moved the furthest from the resonance frequency of 1.15Hz was that of the N4SID model, for a tank frequency of 1.25Hz, and the smallest difference was observed with the ARMAX model for a tank frequency at 1.30Hz

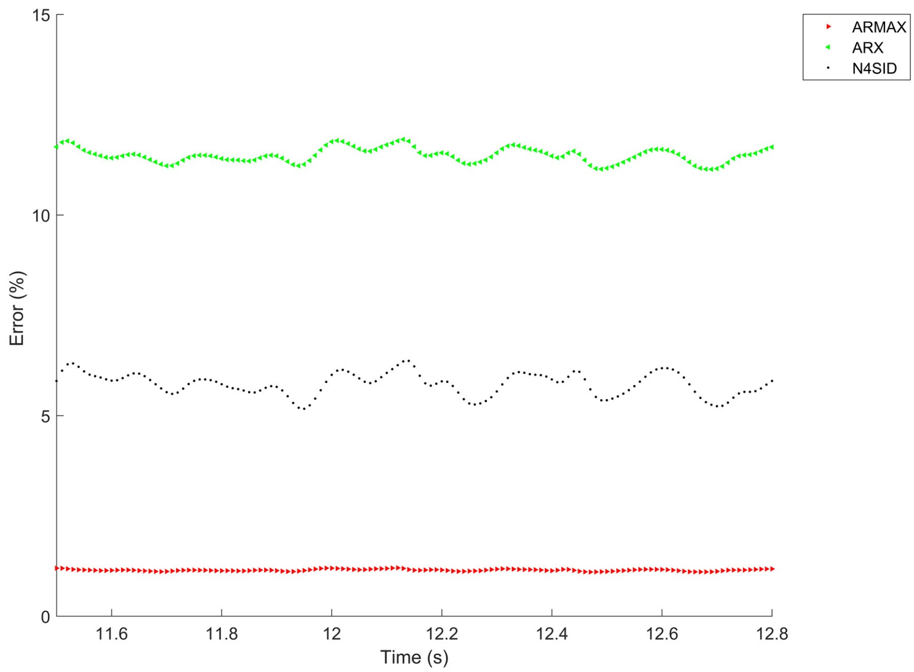

Figure 6. Percentage error distribution at 1.15Hz

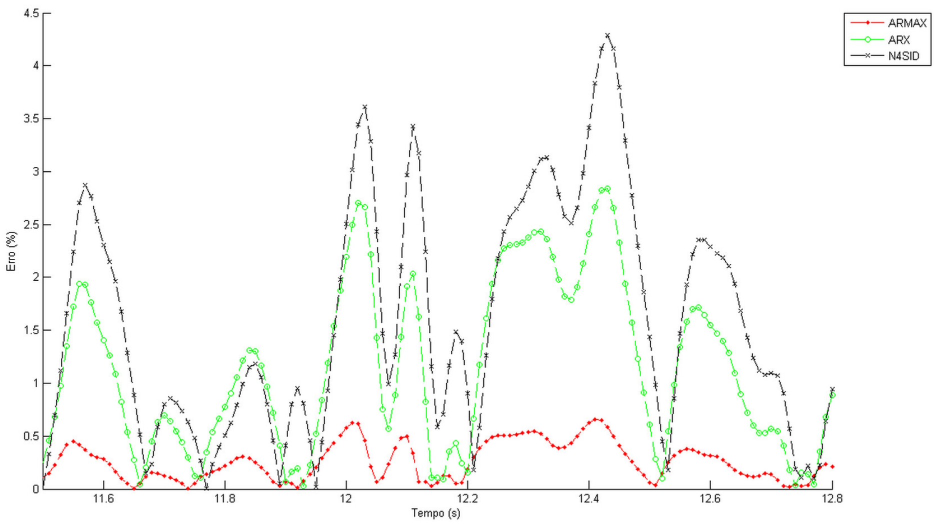

Figure 7. Percentage error distribution at 0.9Hz

The identification methods presented approximate solutions with best results coming from the ARMAX model for the estimation of W_n, which showed a range of error of 0.87 to 21.2%. The ARX model presented an error range of 2.0 to 23.9% and the N4SID model presented an error range of 5.5 to 77.5%.

Table 2. Average error and Error Variance of each model.

Frequency of the test tank $[Hz]$	Average Error ARX $[\%]$	Error Variance ARX $[\%]$	Average Error ARMAX $[\%]$	Error Variance ARMAX $[\%]$	Average Error N4SID $[\%]$	Error Variance N4SID $[\%]$
0.80	1.031	0.931	0.235	0.051	1.439	1.642
0.85	1.027	1.359	0.272	0.099	1.345	1.991
0.90	0.514	0.426	0.117	0.023	0.684	0.582
0.95	0.997	0.997	0.241	0.241	1.309	1.309
1.00	1.445	3.949	0.329	0.211	2.101	5.304
1.05	1.146	2.889	0.262	0.155	1.629	5.350
1.10	1.301	5.268	0.342	0.360	1.809	9.082
1.15	1.187	1.187	0.297	0.297	1.425	1.425
1.20	1.055	2.017	0.246	0.113	1.493	2.995
1.25	1.013	4.026	0.281	0.302	1.317	4.568
1.30	0.791	0.779	0.185	0.043	1.089	1.316
1.35	1.669	2.382	0.381	0.128	2.553	5.254

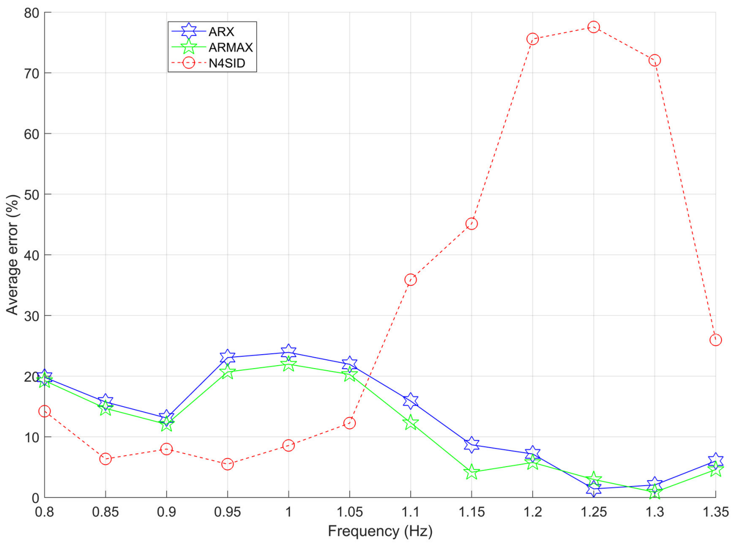

Figure 8. Average models error

Table 3. Average Error of the Natural Frequencies of each model.

Frequency of the test tank $[Hz]$	Frequencies Natural ARX $[Hz]$	Average error ARX $[\%]$	Natural Frequencies ARMAX $[Hz]$	Average Error ARMAX $[\%]$	Natural Frequencies N4SID $[Hz]$	Average Error N4SID $[\%]$
0.80	0.922	19.823	0.928	19.274	0.986	14.230
0.85	0.969	15.743	0.981	14.694	1.077	6.360
0.90	0.999	13.113	1.011	12.073	1.058	7.985
0.95	0.885	23.070	0.912	20.704	1.213	5.501
1.00	0.875	23.929	0.897	21.971	1.051	8.574
1.05	0.897	21.959	0.917	20.297	1.291	12.259
1.10	0.967	15.909	1.008	12.339	1.563	35.909
1.15	1.050	8.686	1.102	4.171	1.669	45.138
1.20	1.067	7.179	1.084	5.773	2.019	75.591
1.25	1.134	1.423	1.184	2.970	2.042	77.565
1.30	1.126	2.066	1.140	0.878	1.979	72.083
1.35	1.081	6.024	1.097	4.608	1.449	25.980

4. CONCLUSION

A comparison of identification models was made over experimental data of a prototype boat to estimate its natural frequency, which was previously known.

We verified that the ARMAX model obtained the results with less average error to the natural frequencies of the models inside the spectrum of entry frequency, showing a better performance than the ARX and N4SID models.

Although the error bands were significant for both the ARMAX and ARX models, ARMAX presented a mean error of 1.6 % in the resonance condition, while the ARX model showed an average error of 8.7 % in this same condition. This comparative result qualifies the ARMAX model as a suitable identification tool for future work.

N4SID had a smaller average error for the tests at lower frequencies; however, it presented a great discrepancy around the frequency of resonance that is the critical factor for the stability of the vessel, which disqualifies it for future works.

We observed that N4SID was the model with the lesser precision on the identification of natural frequency, which can mean that the model is robust to white noise and polarized to colorful noise. Therefore, this alternative is not viable to the desired application, since it has suffered direct influence on Wn medium error. Besides, even with a medium error bigger than ARMAX measurements, it presented a medium error in the Wn, ARX showed an error near ARMAX

Knowing the fundamental frequency of the prototype boat allows us to develop a low cost, easy-building stabilization system, passive but adaptive, which is indicated for future projects.

In this work a controlled input signal was used to generate experimental data. Real boat signal excitements produce a quite complex function. Model identification needs to estimate the input excite signal to find his targets. This is a challenger for further works.

5. ACKNOWLEDGEMENTS

We are grateful to the Fapeam development agency, who supported this work through grants for research and the IFAM-CMDI Research Coordination for the support offered.

6. REFERENCES

Aguirre, L.A. 2007. Introdução à Identificação de Sistemas. Universidade Federal de Minas Gerais, Belo Horizonte. Vol. 3, pp. 219-244.

Coelho, A.A.R., Coelho, L. S. 2004. Identificação de Sistemas Dinâmicos Lineares. Universidade Federal de Santa Catarina, Florianópolis. Vol. 1, pp. 27-39.

Gawad, A.A., Ragab, A.S.; Nayfeh, A.H.; Mook, D.T., 1999, Roll stabilization by anti-roll passive tanks, Ocean Engineering, p. 457469.

Kitamoto, T., Yamaguchi, T. On the Hankel Singular Values for a Parametric System. SICE Annual Conference 2008.

Ljung, L. 1999. System Identification Theory For the User, Appendix4A, pp 132-134, 2nd ed, PTR Prentice Hall, Upper Saddle River, N. J.

Ricco, R. A. 2012. Identificação de Sistemas Utilizando Métodos de Subespaços. Universidade Federal de Minas Gerais, Belo Horizonte.

Rylo, M. N., Soares, F. J. A., Vidal Filho, W. B. 2016. Análise de Desempenho de Tanque de Estabilização Passivo em Embarcações Regionais. Conem.

Van Overschee, P., De Moor, B. 1993. N4SID: Numerical Algorithms for State Space Subspace System Identification. Proceedings of the World Congress of the International Federation of Automatic Control, IFAC, Vol. 7, pp. 361-364, Sydney, Australia.

Van Overschee, P., De Moor, B. 1996. Subspace Identification of Linear Systems: Theory, Implementation, Applications, Kluwer Academic Publishers.

7. RESPONSIBILITY NOTICE

The authors is the only responsible for the printed material included in this paper.