APPLICATION OF MULTILAYER NEURAL NETWORKS FOR REDUCING DATA ACQUISITION TIME

José Aristides dos Santos Machado
Federal University of Para
Computation and Electrical Engineering Department – Av. Augusto Corrêa, 01
66075-110 Belém – Para - Brazil
e-mail: josearistides@gmail.com

Hiran de Melo
Federal University of Campina Grande
Informatics and Electrical Engineering Center – Av. Aprígio Veloso, 882
58109-970 Campina Grande – Paraiba - Brazil
e-mail: hiran@dee.ufcg.edu.br

Petrônio Vieira Júnior
Federal University of Para
Computation and Electrical Engineering Department – Av. Augusto Corrêa, 01
66075-110 Belém – Para - Brazil
e-mail: petronio@ufpa.br

Raimundo Carlos Silvério Freire
Federal University of Campina Grande
Informatics and Electrical Engineering Center – Av. Aprígio Veloso, 882
58109-970 Campina Grande – Paraiba - Brazil
e-mail: rcsfreire@dee.ufcg.edu.br

Francisco Ferreira Santos
Federal University of Campina Grande
Informatics and Electrical Engineering Center – Av. Aprígio Veloso, 882
58109-970 Campina Grande – Paraiba - Brazil
e-mail: ffsantos@dee.ufcg.edu.br

Abstract. *This paper discusses a new strategy for improving the dynamic parameters estimation of a flexible mechanical structure represented by a Multiple Degree of Freedom System (MDOF) model. The improvement refer to the Frequency Response Function (FRF), obtained by measuring the mechanical system impulse response. The hypothesis of this study is that the considered model (mechanical model) is suitable to describe the system. Therefore, an efficient method for obtaining experimentally the FRF should give a significant conformity between the theoretical FRF and the experimental FRF. This study investigates the quality improvement obtained by increasing the virtual acquisition time (forecasting). Such strategy makes use of Linear Predictors (ARX and ARMAX models) and Non Linear Predictors (Multilayer Neural Networks). Results obtained from graphics and tables suggest that Multilayer Neural Networks are feasible for this use.*

Keywords: *Vibration, Parameter Estimation, Forecasting, Multilayer Neural Networks.*

1. INTRODUCTION

The monitoring of structures and equipments is part of a scientific field named Structural Integrity Evaluation, which comprehends the application of methods and procedures to diagnose any damage in a structure, to predict its behavior and indicate its monitoring needs, inspection or recuperation, in order to prolong its useful life and consequently avoid its functionality loss. (Freire et al., 1994). To make this evaluation, it is generally necessary to perform several tests, by measuring parameters and the response of materials that compose the structure. In consequence of those tests, it is necessary to interrupt the local routine for sometime.

In places such as highway bridges, footbridges, dams, offshore petroleum platforms, manufactures, industries, among others, long interruptions to perform structural tests may cause considerable damages (i.e. bothering people, offering risk of accidents while not using footbridges) and economical damages (i.e. profit reduction, due to the decrease of production), (Pimentel, 1997). Therefore, referring to structures vibration, new methods are necessary to reduce the stop time in data acquisition.

Acquisition methods that make use of the Frequency Response Function (FRF) establish a relationship between the system response in displacement, speed or acceleration and its respective inputs, which generally are impulsive forces (MCconell, 1995). Several studies have been using Multilayer Neural Networks (MLNN) in FRF data analysis.

WU et al. (1992) has identified damages in a three steps building selecting the 200 initial points o the FRF as input for a MLNN. In Melo's (2002) study, an estimate of the system frequency response has produced a better result by SPI, than using linear predictors, when considering simulations with experimental data, without needing a previous model of the structure.

This study contribution is the investigation of MLNN application in flexible structures data analysis. Instead of vibration signal acquisition equipments, simulations based on the flexible structure model are applied to acquire data. The acquisition of vibration signal is made by sampling the system impulse response. The system is represented by the Two Degrees of Freedom (2DOF). The system mechanical model, which is the simplest from Multiple Degrees of Freedom (MDOF).

2. IDENTIFICATION OF FREQUENCY RESPONSE FUNCTION

Consider a 2DOF system, represented in Figure 1 with the following element values: m1 = m2 = m3 = 10kg, c1 = c2 = c3 = 3 N.s/m and k1 = k2 = k3 = 1600 N/m.

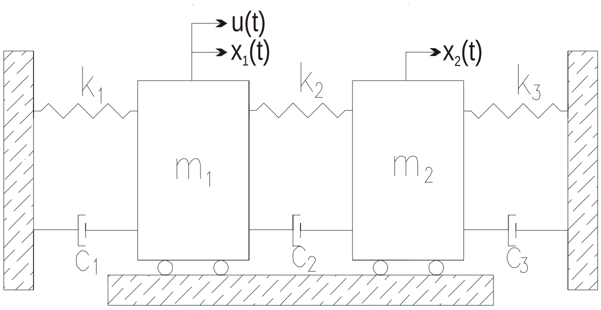

Figure 1. Representation of a 2DOF model

The Transfer Function for the displacement produced by an external impulsive force u(t) in m1 is presented in equation (1):

$$H(s) = \frac{X_1(s)}{U(s)} = \frac{0,1s^2 + 0,06s + 32}{s^4 + 1,2s^3 + 640,27s^2 + 288s + 76800} \tag{1}$$

Applying the inverse Laplace transform to equation (1), yields:

$$x_1(t) = 0,0022sen(21,9043t)\exp(-0,45t) + 0,0040sen(12,6482t)\exp(-0,15t) \tag{2}$$

Equation (2) is used in the simulation to obtain the “acquired” samples at each 0.0313 s (T / na = 1/32 s). In discrete time, this equation is named Vibration Measuments Simulator. For the case currently studied, the system natural frequencies may be calculated by (Thomson, 1998) the equation (3):

$$\omega_{n1} = \sqrt{\frac{k}{m}} \quad ; \quad \omega_{n2} = \sqrt{\frac{3k}{m}} \tag{3}$$

In FRF estimation, the Fast Fourier Transform (FFT) algorithm has been used. It calculates the Discrete Fourier Transform (DFT) of the discrete signal. From discrete DFT points, a FRF estimate for the system is obtained. Let *x* be a vector with N samples obtained in T seconds. Its DFT is a vector with the same length, whose elements are obtained from equation (3) (Oppenheim et al., 1997).

$$X(k) = \left[\frac{1}{N} \sum_{n=1}^{N} x(n) \exp\left(\text{-j } \frac{2\pi(\text{k-1})(\text{n-1})}{\text{N}} \right), \quad 1 <= \text{k} <= \text{N} \right] \tag{4}$$

The FRF is a continuous curve. However, as it was estimated from a discrete signal, a FRF discrete time version is represented in Figure 2. The continuous estimate may be obtained by linking the discrete FRF points. Therefore, reliable results in the frequency domain are obtained only when the acquisition time (number of samples) is relatively large. Thus, the larger the amount of available informations about the 2DOF model FRF, the better will be the estimate.

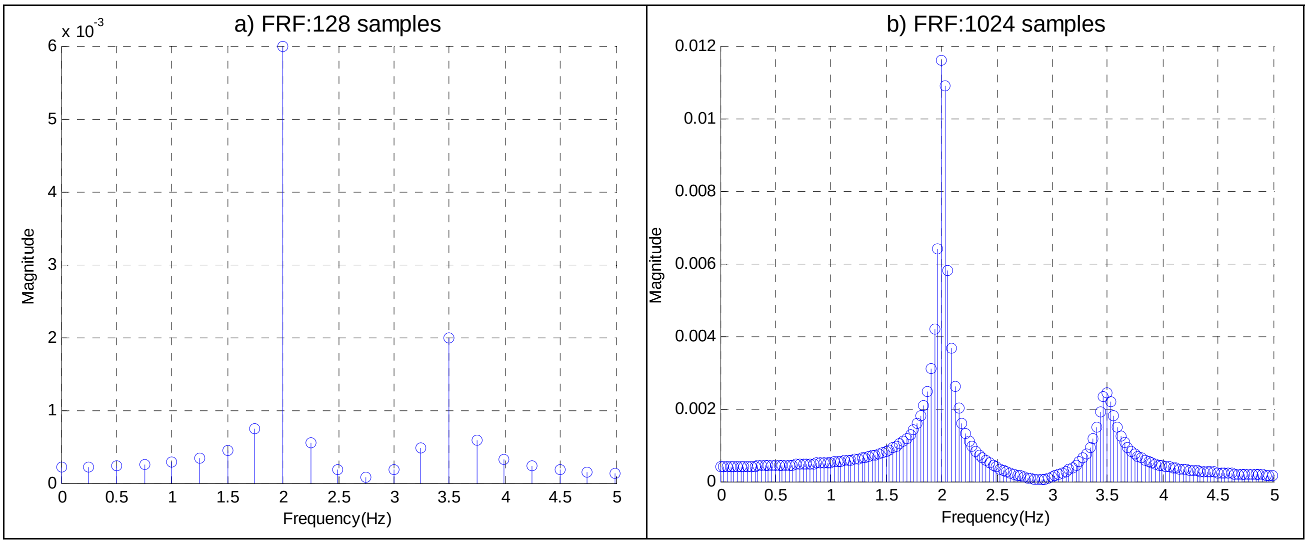

Figure 2. Discrete time FRF version: a) 128 samples; b) 1024 samples.

The spacing between spectral lines is called frequency resolution, whose formal definition is given in equation (5).

$$\Delta f = \frac{f_a}{N} \tag{5}$$

Where $f_a = 1/\Delta t$ the sampling frequency (number of samples per second), Δt is the time gap between two successive samples, N is the total number of samples. As $N = f_a T$, where T is the total acquisition time of the signal, so $\Delta f = 1/T$. Therefore, to improve the frequency resolution, the total acquisition time must be increased.

Observe again Figure 2, in which the absolute value DFT graphics were drawn from samples acquired at a ratio of 32 samples/s. In Figure 2.a, it is shown the DFT obtained from 128 samples (equivalent to 4 s), resulting in a frequency resolution of 0.25 Hz. In Figure 2.b, it is shown the DFT obtained from 1024 samples (equivalent to 32 s), resulting in a frequency resolution of 0.0313 Hz. Finally, it must be noticed that the FRF estimates have their frequency resolution limited by the conditions of the signal acquisition (acquisition time), whereas in the mechanical model FRF that limitation does not exist.

In Figure 3, it is shown a comparison between the graphic of the FRF estimated with 128 samples and the FRF of the ideal mechanical model.

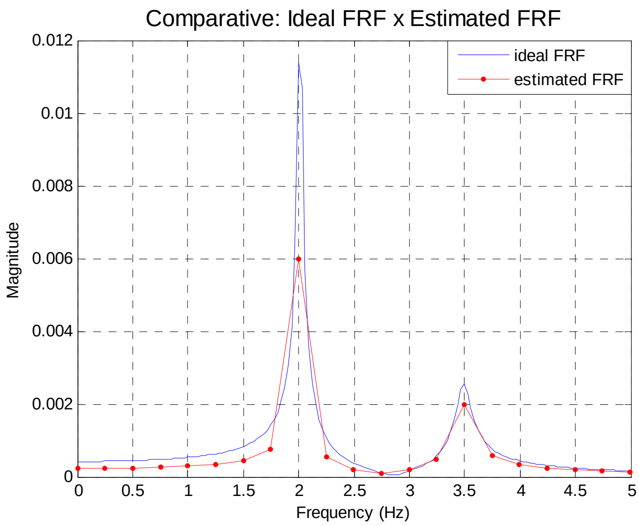

Figure 3. Comparison between the ideal FRF and estimate FRF from the signal obtained by simulation.

In the experimental obtaining process of the model through FRF, it is necessary to find the natural frequencies and damping ratios. The 2DOF mechanical model has two vibration modes, what results in the existence of two natural frequencies. An immediate estimate for the natural frequencies consists in identifying them as the frequencies in which occur the peaks of absolute value of the system impulse response FRF (Thomson, 1998). The damping ratios may be estimated by using the half power bandwidth method, in which the level 3 dB below each FRF peak corresponds to the half power point. (Rao, 1995). The larger the damping, the larger is the frequency range between these two points, as it is shown in Figure 4.

$$\varsigma = \frac{\omega_2 - \omega_1}{2\omega_n} \tag{6}$$

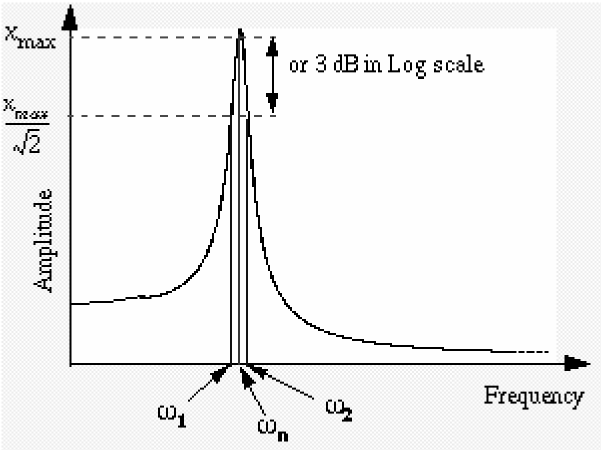

Figura 4. Half Power Bandwidth Method

3. LINEAR METHOD

To improve the quality of FRF estimate, it is convenient to enlarge the number of samples. This may de done by increasing the real data acquisition time or by using prediction methods. Using the linear method, similar to Ljung's (1987), from 128 samples and a 0.0313 s sample interval, results in the identification of the ARX model type, with the following representation in discrete time domain:

$$G(q,\theta) = \frac{B(q)}{A(q)} = \frac{0{,}0002481q^{-2} + 0{,}0002481q^{-3}}{1 - 3{,}3726q^{-1} + 4{,}7835q^{-2} - 3{,}3077q^{-3} + 0{,}9634q^{-4}} \tag{7}$$

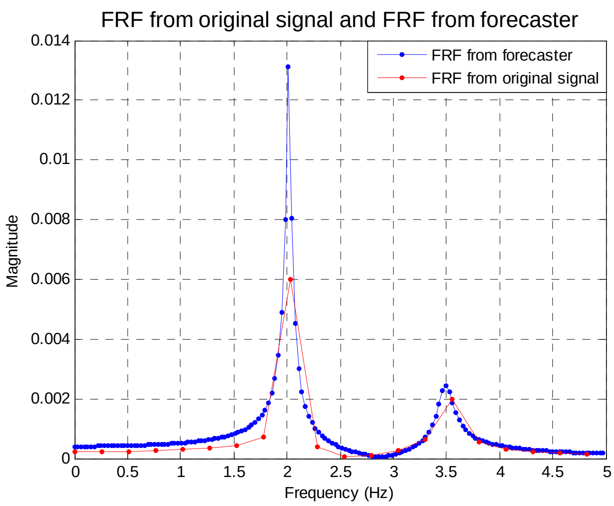

Figure 5. Comparison between the estimates using a linear predictor.

Equation (7) was then an algorithm for future signal values estimation. From this equation, 896 samples have been generated, in addition to the 128 previous samples. In Figure 5, it is shown a comparison between this new estimate and the original signal FRF.

4. NONLINEAR METHOD

The use of the nonlinear method eliminate the previous need for knowing the structure model, what, for multiple degrees of freedom systems is more suitable, due to the many variables involved on it.

Among the strategies that allow the application of MLNN in the FRF estimation of a structure with a reduced number of the vibratory signal samples, it was used the training approach by windowing (Melo, 1996).

The proposed prediction strategy consists in dividing the set of 128 consecutive samples in 16 subsets with 8 samples (windows), as shown in Table 1. Applying in the MLNN a window per time, in the next step, the window that was used as target it starts to use as input. This way, the set of training windows constituted is shown in the Tab. 2.

Table 1. Discrete signal windowing

Windows	Signal Samples
Win1	$x_1 x_2 .... x_8$
Win2	$x_9 x_{10} .... x_{16}$
$\vdots$	$\vdots$
Win16	$x_{121} x_{122} .... x_{128}$

Table 2. Set of training windows

Set of Input Windows	{Win1, Win2, ... ,Win15}
Set of Target Windows	{Win2, Win3... ,Win16}

From these tests, it can be verified that a MLNN composed by 3 neurons in the input layer and 8 neurons in the output layer has produced satisfactory results. The MLNN architecture is shown in Figure 6.

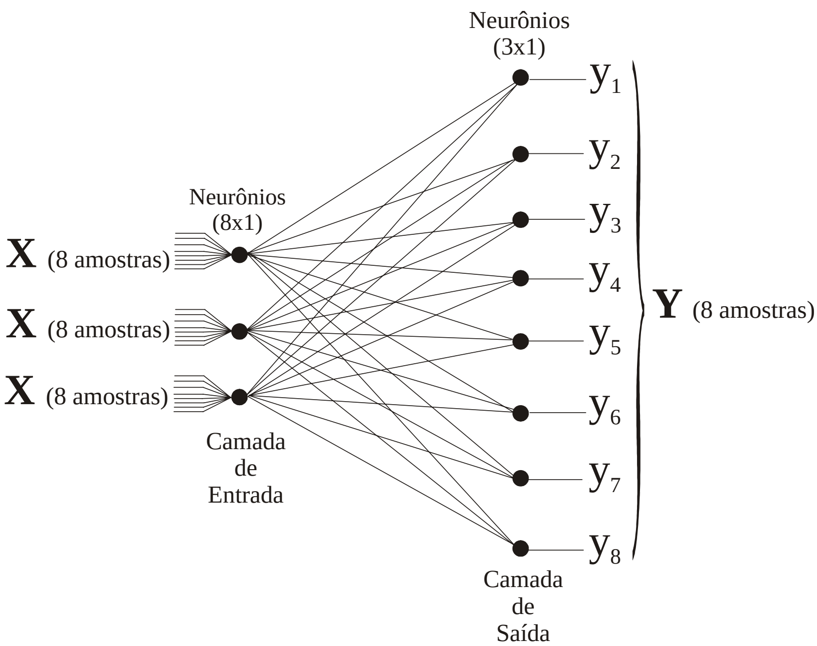

Figure 6. Representation of the MLNN used in the prediction.

The implemented training algorithm was the “backpropagation Levenberg Marquardt” (Hagan et al. 1994). The algorithm Levenberg Marquardt provides a good benefit between the speed of Newton’s method and the guaranteed convergence of the steepest descent.

5. TESTS AND RESULTS

In Figure 6, the results described in both time and frequency domains are shown. In Figure 6.a, it is shown the improved discrete signal (32 s), comprehending the signal originated from the mechanical model (4 s, in red) and the further 896 samples (28 s, in blue), generated by the MLNN. In Figure 6.b, it is shown in blue the FRF estimate, produced by the addiction of the samples (from the initial 128 to 1024) obtained through the neural predictor and, in red, the FRF estimate, which is compared to the 128 samples produced from the representative 2DOF model.

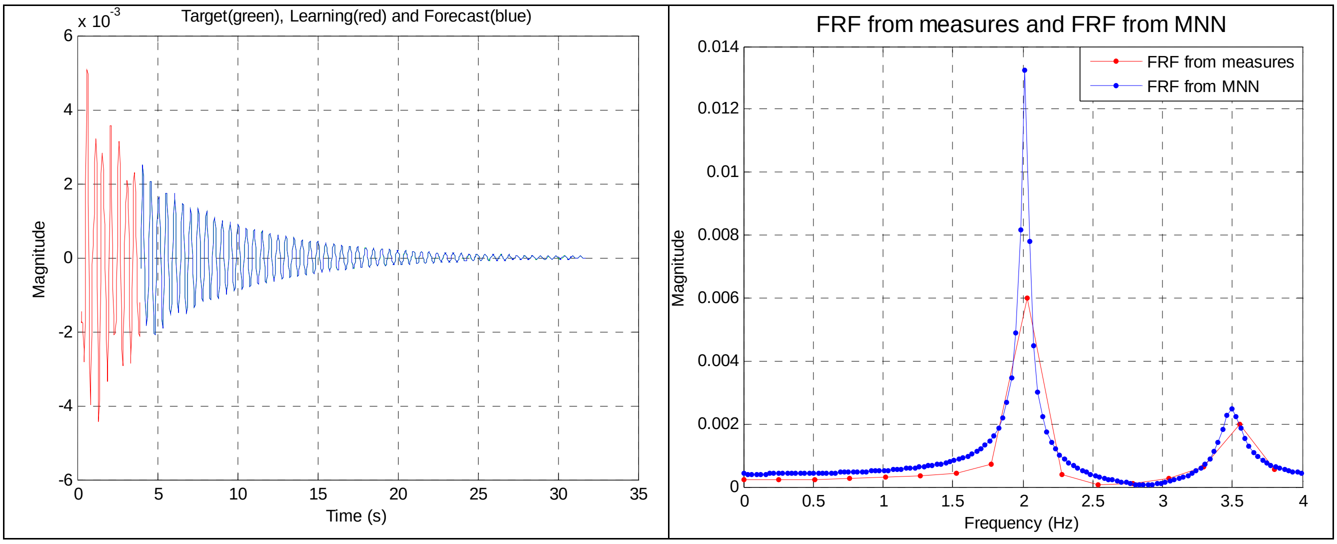

Figure 6- a) The signal that was improved via neural predictor; b) Comparison between both of the FRF.

To evaluate the MLNN training performance, not only comparative graphics, but also a quantitative comparison through the root mean square error (RMS) is available. In Table 3, the RMS values of the ideal mechanical model FRF for the studied estimates are shown. A new FRF estimate, the one that added samples through the Measurements Simulator, is also in Table 3.

Table 3: Comparison of RMS values

Estimate	RMS*10-7
Original Signal (128 samples)	126
Enlarged Signal via 2DOF Neural Predictor (1024)	2,1
Enlarged Signal via 2DOF Linear Predictor (1024)	3,7
Enlarged Signal via SM (1024)	2,1

From the analysis of the comparative graphics and Table 3, it is verifiable that the MLNN is able to enlarge the samples sequence with a performance similar to the linear preditors’ and similar to the Measument Simulator itself. These results show that the MLNNs are effective in the parameters estimate of flexible structures

5.1 Gaussian white noise

To investigate the measurement error influence over the methods used for the FRF estimation improvement, a addictive Gaussian white noise has been added to the signal, as shown in Figure 7.

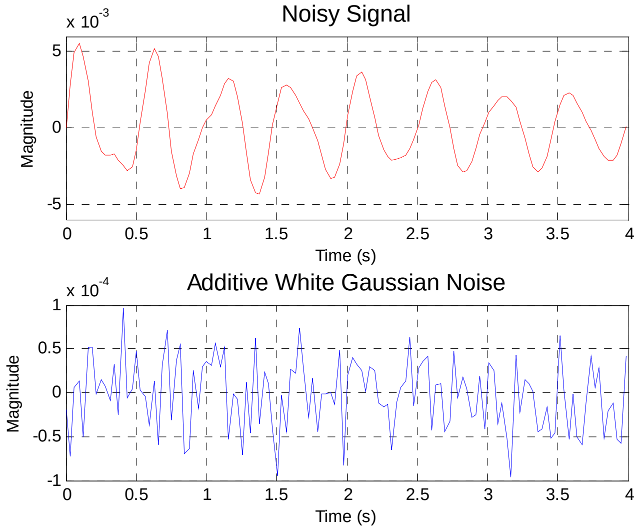

Figure 7. Noisy signal and addictive Gaussian white noise

In linear prediction, the models Family ARX did not characterize as compatible with the nature of the simulated signal, i.e., a disturbed signal. Therefore, the models Family ARMAX was chosen for the study (Ljung, 1987).

The obtained ARMAX model, identified from 128 samples and a uniform sample interval of 0.031 s, represented in the time domain, is given in equation (8).

$$\frac{0{,}0002126q^{-1}+0{,}0001917q^{-2}+0{,}0001579q^{-3}}{1-3{,}3062q^{-1}+4{,}6082q^{-2}-3{,}1452q^{-3}+0{,}9116q^{-4}} \tag{8}$$

In Figure 8, estimates obtained with the original signal and with the enlarged signal are shown. The estimate curve with the enlarged signal illustrates the effective improvement of the FRF quality.

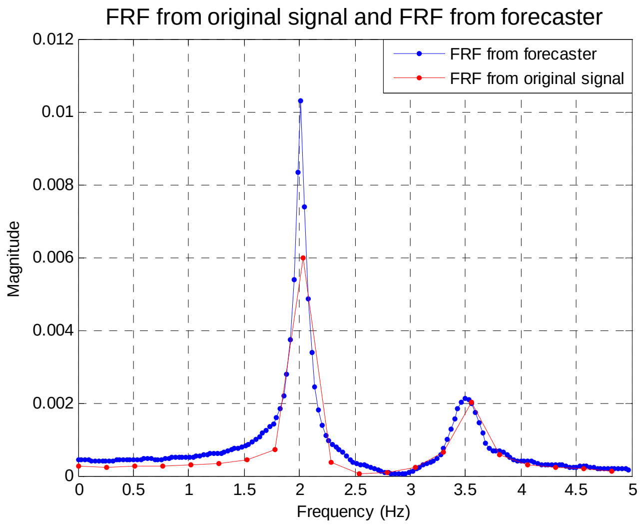

Figure 8. FRF estimate obtained from ARMAX predictor

The verification of the MLNN performance for the improvement of the noisy signal FRF estimate is made by enlarging it through a Network of the same architecture as shown in Figure 6. The estimated FRF is shown in Figure 9.

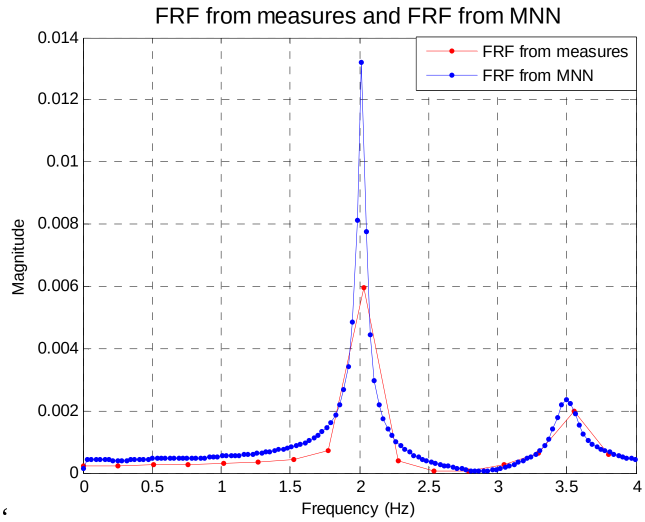

Figure 9. FRF estimate FRF obtained from a MLNN

6. CONCLUSIONS

From the analysis of the results, by means of graphics and tables with the MLNNs performance index, it was verified that they have the same prediction characteristics as the linear predictors based on ARX and ARMAX models, not only qualitatively but also quantitatively. Concerning the linear prediction models used for performance comparison, the ARX predictor presented a satisfactory result when considering the signal without disturbs, and for the disturbed signal the ARMAX predictor presented the acceptable results.

The performance obtained with the analyzed neural network and the step training strategy shows an effective improvement in the estimation of a flexible structure parameters.

These results are limited to the fact that the signals were simulated from 2DOF models. It is also remarkable the consideration of the external force in a single point of the mass in the applied models and the constant and equal values attributed to the spring and the damper elements. Still, the measurement errors limitations refer to the fact that the errors were simulated by the addictive Gaussian white noise added to the signal.

7. ACKNOWLEDGEMENTS

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