Towards a methodology to estimate environmental loadings from time history motions of offshore platform by using Artificial Neural Networks

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Abstract. Floating production systems (FPS) for offshore oil exploration are subject to environmental loads such as waves, wind and current in different directions of incidence and varying intensities that result in dynamic movements of this same system. Nowadays, FPS has several sensors, in this particular case, its position is monitored by GPS and accelerometers. On the other hand, it is hard to monitor environmental loadings in a deep water that depends on oceanographic buoys. Therefore, this paper presents the first steps to estimate the parameters of wave loading from a time history motions of an offshore platform by using Artificial Neural Networks (ANN). From this, it may be possible to verify oceanographic forecast models and to know the environmental conditions at the moment of an event, such as, line break or equipment breakdown. In addition to this, we can estimate real environmental data for the generation of digital twins, which is a digital replica of the real system. In the case study, ANN training process is performed from data of a rigorous Finite Element (FE) analysis. From the results, we can observe that ANN presents a high level of accuracy in this kind of application, which allows to move forward with research in this area.

Keywords: Environmental loadings, Artificial Neural Networks.

1 Introduction

Floating production systems (FPS) are currently established as the main option for offshore oil production activities. These systems are subject to extreme and operational environmental loadings of waves, wind and current acting in different directions of incidence. In general, such loadings are the main factor causing dynamic movements in the FPSs. Today, FPSs have various sensors capable of measuring, among other quantities, its position in six degrees of freedom. On the other hand, measuring environmental loads in ultra-deep water is hard depending on oceanographic buoys.

Thus, this work presents an application of Artificial Neural Networks towards to estimate environmental loadings from time history motions of an offshore platform. In other words, the vessel can be used as an oceanographic buoy and, based on its movements, estimate the acting environmental loads.

In this pilot study, only the wave load is considered, and all input data of the ANN model were obtained by rigorous nonlinear dynamic analysis by the Finite Element Method.

In recent years, applications of Artificial Intelligence have gained popularity in oil & gas offshore engineering. Several types of complex problems have been successfully solved by such methods; for instance Pina [1] relates the present value of the desired tension time series, not only to present and past values of the exogenous series (platform motions), but also to past values of the desired series itself, associating an ANN with a Nonlinear AutoRegressive model with eXogeneous inputs (NARX). In [2] new meta-models for the uncoupled analysis of mooring lines and risers were devised, based on wavelet networks (WNs) instead of ANNs. Platform motions are used to estimate the parameters of the structural response of the lines by ANN [3, 4] and wavelet network in [3]. ANN and Kriging models were investigated by [5] to predict the performance of a moored floating vessel under the full spectrum of metocean conditions, and uses this capability to detect a single mooring line failure or a loss of station event. In [6] the authors proposed a meta-model based on ANN to predict damage of mooring lines using detection of subtle shifts in the long drift period of a moored floating vessel as an indicator of mooring line failure, using only GPS monitoring (platform motions). In [7] the authors extends the approach presented in [6] to a spread-moored FPSO with varying draft for a complete range of environment directions.

2 Assembly of the metamodel

2.1 ANN Basic formulation

Artificial Neural Network is one of the most famous and widely used function learning algorithms and it is inspired by biological central nervous system that consists of interconnected neurons. ANNs are computational models based on mathematical regression capable to predict outputs, given a certain input. Neurons is an important part of the method; they are composed by mathematical functions that receive inputs and return an output. They are organized in layers where each layer has the same connections on its neurons and the same type of output. Figure 1 represents an artificial model of a neuron [9].

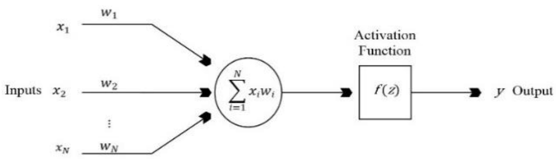


Figure 1. Mcculloch-Pitts Neuron [9]

Recurrent networks can be formed when the output of a neuron is received by other neurons without restrictions. Moreover, when only the next layer neuron on the network can receive the output, a feed-forward neural network is formed as shown in Figure 2.

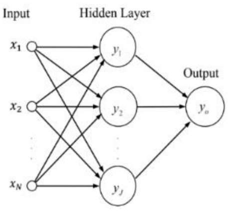


Figure 2. General structure of two layers feed-forward Artificial Neural Network [1]

Thus, ANN training process consists in a procedure for adjusting the connection weights of an ANN. One example of this type of algorithm is Levenberg–Marquardt [**Erro! Indicador não definido.**, **Erro! Indicador não definido.**], which provides a numerical solution to the problem of minimizing a nonlinear function. It is fast and has stable convergence.

2.2 Autoregressive model (AR)

A large number of time series exhibit serial autocorrelation; that is, linear association between lagged observations. So, AR model can be indicated for solving linear time series problems. This method depends on a number of past observations, called *delays*, to predict the current response of the time series.

2.3 Exogenous model

Exogenous method consists in predict the desired time series with the help of exogenous inputs (other different series). In this work, the exogenous inputs are the motion series of the vessel, that is: surge, sway, heave, roll, pitch and yaw series.

2.4 Nonlinear autoregressive exogenous model (NARX)

When the goal is time series prediction, a good alternative consists in associate ANN with a Non-linear Auto Regressive model with eXogenous inputs (NARX) [12]. Such approach relates the present value of the desired time series not only to the present and past values of exogenous series, but also to the past values of the desired series itself (*delays* as mentioned above), and a residual term.

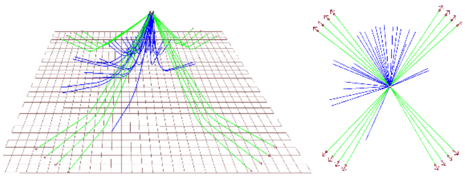
It should be recalled that, in this paper the exogenous inputs are the motion series of the FPS and the variable of interest is the wave elevation series. We consider that the residual term is set to zero.

The ANN is trained using the MathWorks' Matlab Toolbox [13] with NARX model.

3 Case study

3.1 Characteristics of the FPS

ANN are applied to estimate the time series of wave elevation from the displacements of the FPS. The platform, installed at a water depth of 1800 m, is moored by 16 lines in a conventional catenary configuration, which is similar to the employed in deep water in the Campos Basin, Southeastern Brazil. Figure 3 (a) presents a schematic tridimensional view of the platform with its mooring lines (depicted in green) and risers (depicted in blue), while (b) shows a top view. The composition of the lines is not important to this problem, since it is constant. However, the description of the lines segments can be found in [2].



(a) (b)

Figure 3. FPS for ultra-deepwater scenarios, (a) 3D view and (b) Top view

A schematic view of the hull can be seen in Figure 4, and the main characteristics are shown in Table 1.

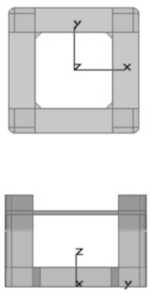


Figure 4. Platform hull, top and front views

Table 1. Characteristics of the Hull

Element	Value
Length [m]	97.0
Breadth [m]	97.0
Height (until main deck) [m]	75.0
Distence between center of columns [m]	75.0
Pontoons (length × height × width) [m]	52.0×11.5×25.0
Heading, relative to north [degrees]	90
Operational draft [m]	34.0
CoG (X, Y, Z) [m]	0, 0, 31.5
Total weight [kN]	940,000

3.2 Inputs for the surrogate model

<u>Model data</u>

As mentioned before, the inputs required by ANN metamodel with NARX approach are the platform motion time series (surge, sway, heave, roll, pitch and yaw) and a short initial window of the desired output time series (i.e. wave elevation). These data were provided by a coupled motion analysis performed using PROSIM [14] program. This program incorporates, in the same computer code and data structure, hydrodynamic models for the representation of the hull, coupled to a FE model to represent the hydrodynamic and structural behavior of the mooring lines and risers. The wave loads are represented by an irregular seastate defined by the JONSWAP [15] spectral model with the following parameters: significant height Hs = 5.56 m and peak period Tp = 12.5 s aligned with the local y-axis of the platform. This seastate produces a wave elevation series (which it is the ANN output) and the short window is shown in Figure 5. The analysis is performed for a total simulation time of 10,800 s, using a time step of 1 s. Figures 6 and 7 presents short window of the resulting of these motions.

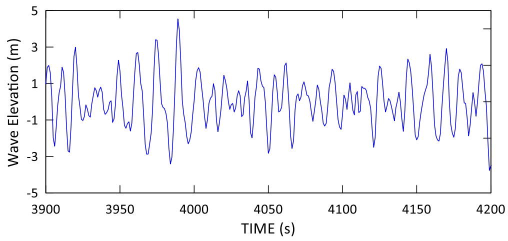
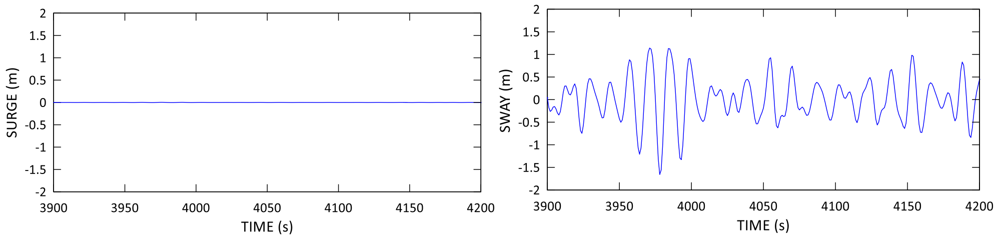
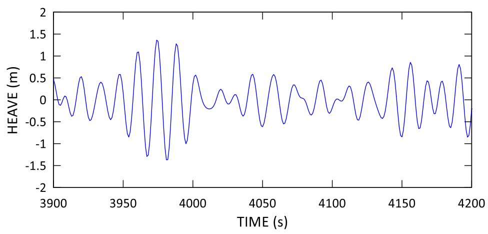


Figure 5. Window of the time history of Wave Elevation



(a) (b)



(c)

Figure 6. Window of the motion series: (a) Surge, (b) Sway and (c) Heave

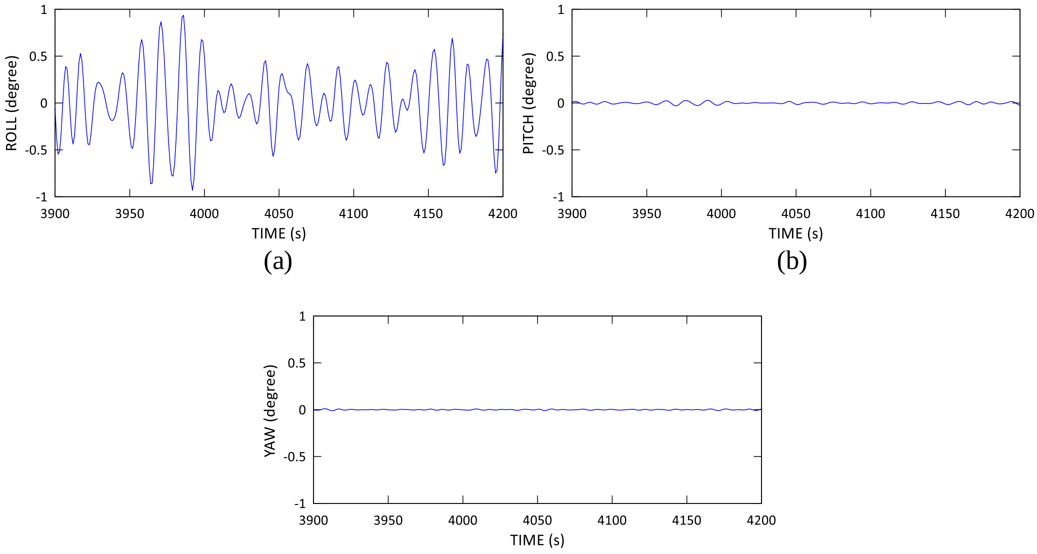


Figure 7. Window of the motion series: (a) Roll, (b) Pitch and (c) Yaw

<u>ANN configuration</u>

In addition to assessing the accuracy of the metamodel applied to the current problem, a parametric study of delay was performed. Thus, the other ANN parameters were arbitrated and kept fixed while the delay varied. Table 7 shows the configuration of the Artificial Neural Network used in the case study.

Table 2. Artificial Neural Network configuration

Parameter	Type/Value
Training Algorithm	Levenberg Marquardt
Neurons	30
Dataset size	10,800
Training set (80%)	8,640
Validation set (15%)	1,620
Test set (5%)	540

3.3 Results

<u>Parametric study: delays</u>

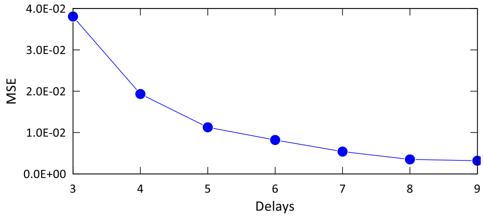
As above mentioned, delays can be defined as the number of previous points of the input series used in the prediction. Here, were applied the same delays for all input data. Recalling that the training/validation of the ANNs involves the random initialization of the weights, each delay is assembled 10 times using different random seeds.

The error measures are consolidated in Table 3, in terms of mean of the 10 runs of Mean Square Error (MSE), correlation factor *R* and CPU time.

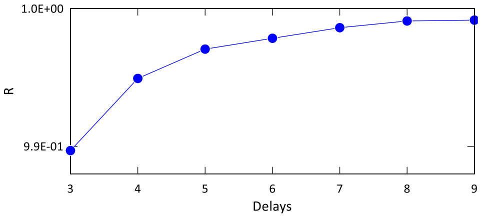
We can note that, in Table 3, all error reported are small, indicating the good performance of the ANNs. The best result was obtained by delays equal to 9. It is important to cite that over 8 delays MSE and R tend to stagnate as time continues to increase. Figure 8 allows a visual assessment of delays results.

Table 3. Performance of ANN metamodel (mean of 10 independent runs)

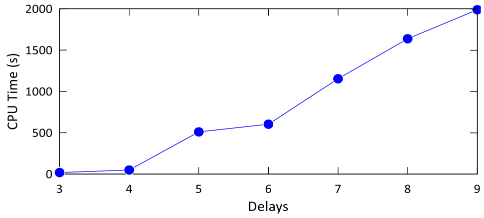
Delays	MSE	R	CPU Time [s]
3	3.8080E-02	9.8969E-01	18
4	1.9328E-02	9.9493E-01	49
5	1.1267E-02	9.9706E-01	510
6	8.1941E-03	9.9784E-01	603
7	5.3839E-03	9.9861E-01	1153
8	3.4970E-03	9.9910E-01	1637
9	3.1782E-03	9.9916E-01	1988



(a)



(b)



(c)

Figure 8. (a) MSE Evolution vs Delays, (b) R Correlation vs Delays and (c) CPU Time vs Delays

<u>Performance of the ANN model</u>

Although test errors be more effective to check accuracy of the method, as depicted in Table 3, it is also interesting to present a visual comparison between the results predicted by the ANN model and the actual results provided by FE analysis. This comparison is presented in Figure 9, in terms of a window of the time series of wave elevation. A remarkably good agreement can be observed.

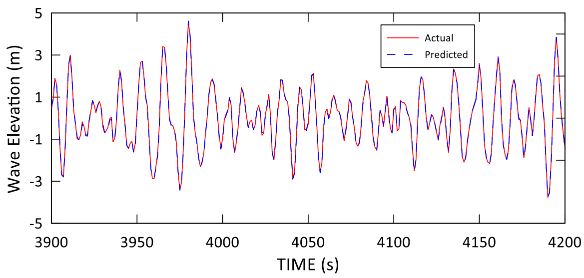


Figure 9. Window of the Wave Elevation: Actual vs Predict Value

4 Conclusions

This work presented a pilot study to develop a methodology to estimate the wave elevation time series from time history motions of offshore platform by using Artificial Neural Networks. To achieve the goal, a metamodel based on ANN with a Non-linear Auto Regressive model with eXogenous inputs (NARX) was used.

Here, this method is applied in a real-world case study in a deep-water scenario. And observing the results, it can be noted that the influence of the variation of the delays is very significative reaching its ideal value at 8. Above that the MSE and R stabilized, and time continued to increase. In any case, the accuracy of the present meta-models in the estimation of the wave elevation is excellent.

Further developments planned in this line of research include predicting in addition to wave, current and wind loads. Thus, one can predict in a single metamodel the environmental loads acting on Floating Production Systems.

Besides that, other enhancements in the metamodels that may be considered in future works include the use of wavelet neural networks instead of standard ANNs to comprise still more accurate surrogate models.

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