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APPLYING WAVELET NEURAL NETWORKS AS SURROGATE MODELS IN THE DESIGN OF MOORED FLOATING SYSTEMS FOR OFFSHORE OIL PRODUCTION

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Abstract. *Floating production systems are more susceptible to dynamic actions, resulting from environmental actions, than fixed platforms. Also due to the high indulgence of these systems, numerical tools had to evolve in order to consider not only the dynamic effects as well as the non-linear effects due to the large displacements which the unit is exposed to. The mooring system must assure a rigidity such that the movement of the unit is minimal, without the involved forces exceeding pre-established safety limits. The dynamic behavior of the structure is represented by time series of the parameters of interest, such as: efforts, tensions, displacements, etc. Wavelet neural network is a combination of the feed-forward neural network architecture with the wavelet transform, and it has been considered as a good alternative for the approximation of non-linear functions. The objective of this research is the application of wavelet neural networks in order to predict the series, replacing the dynamic analysis with finite elements. An extensive experimental evaluation was performed in order to determine the best suited wavelet function and topology for the network. In this way, the purpose is to find results for mooring lines configurations as good as those achieved in a dynamic analysis with finite elements, in considerably less time.*

Keywords: *slender structures, mooring lines, surrogate models, artificial neural networks, wavelet neural networks*

1. INTRODUCTION

With the advance of oil exploitation activities in deep and ultra-deep waters, the use of Floating Production Systems (FPS) based on moored ships or semi-submersible platforms has become more frequent. The design of mooring lines, risers and umbilical cables connected to FPS must comply with pre-established safety limits based on certain parameters of their structural response, such as tensions or stresses.

Since these are slender structures highly susceptible to dynamic effects from the environmental loads, and also to severe non-linear effects mainly due to the large displacements they undergo, those parameters of their structural response must be defined in terms of time series, which are usually obtained from complex Finite-Element (FE) time-domain simulation tools. Moreover, since the environmental loads are non-deterministic, to achieve statistical stability of the results long simulation times must be analyzed (typically 3 hours, or 10800s). Also, the evaluation of fatigue life requires analyses for hundreds or thousands of load combinations. All these factors may naturally lead to excessive computational times, and therefore an increasingly important line of research consists on the development of time-domain computational strategies that present improved efficiency for the nonlinear dynamic analysis of structures (Correa, *et al.*, 2010; Jacob and Ebecken, 1992; Jacob and Ebecken, 1993; Jacob and Ebecken, 1994a; Jacob and Ebecken, 1994b; Rodrigues, *et al.*, 2007; Jacob, *et al.*, 2012a; Jacob, *et al.*, 2012b).

However, on some situations more expedite solution procedures could be required, such as on preliminary stages of design, or associated to optimization procedures by evolutionary methods (Lima, *et al.*, 2005; Pina, *et al.*, 2011; Vieira, *et al.*, 2012). In this latter case, thousands of candidate solutions must be evaluated in order to determine their fitness, which is needed for the evolution process.

Therefore, instead of studying alternative FE-based methods for the determination of the response parameters of slender structures, this paper follows a different approach based on the development of simpler methods – the so-called *surrogate models* or *meta-models* (Jones, 2001). Many practical engineering problems have benefit from such models, especially when difficulties are found in the establishment or application of a mathematical model, and also when associated to optimization procedures. Typical applications include temporal data analysis, where surrogate models can be used to provide a given response, expressed as time series, as function only of some input dada, not requiring detailed knowledge of the dynamic parameters of the system (Pina and Zaverucha, 2008; Ford, *et al.*, 2011).

One of the possible approaches consists on using polynomial models, such as the NARMAX model (***N****onlinear* ***A****uto* ***R****egressive* ***M****oving* ***A****verage with e****X****ogenous inputs*) (Chen and Billings, 1989; Zhu, 2003). Another promising approach related to the use of surrogate models is their association with Artificial Neural Networks (ANN). Such methods have been applied to the prediction of time series for different applications (see for instance Azoff, 1994). ANNs have also been employed in many applications related to ocean and offshore engineering; for instance, in (Mazaheri and Downie, 2005) ANN were employed to predict platform excursions under environmental loadings.

Applications of ANN to the prediction of sea-state characteristics have been presented in (Yasseri, *et al.*, 2010) and the references thereof. An application of ANN for the prediction of capability polar plots for dynamic positioning systems was presented in (Mahfouz, 2006).

Relating specifically to the problems considered in this work (nonlinear dynamic analysis of slender offshore structures), previous works have applied polynomial models in order to replace computationally expensive FE calculations (Sagrilo, *et al.*, 2000; Gobat and Grosenbaugh, 2001; Matos, 2005; Pascoal, *et al.*, 2005). The application of a simple backpropagation ANN was presented in (Guarize, *et al.*, 2007), comprising an "exogenous" method where the desired time series of line tensions is estimated with the help of the time series of platform motions prescribed at the top of the line, and using a short initial window of the line tensions that result of a FE simulation to train the ANN. In (Pina, *et al.*, 2013), it is proposed the use of an ANN working as a Nonlinear AutoRegressive model with eXogenous inputs (NARX). Differently from previous purely exogenous models, the NARX model relates the present value of the desired time series not only to present and past values of exogenous series (i.e. platform motions) but also to past values of the desired series itself. Observing the results of the case studies, it could be verified that the NARX models performed remarkably better than the exogenous models both in terms of accuracy and computational time. This indicates that the NARX approach can be a better alternative for practical uses on estimating the top tensions of mooring lines or risers of FPS (or any other result obtained by a FE simulation), replacing the full use of FE-based numerical tools mainly at preliminary design stages, or associated to optimization procedures by evolutionary methods.

In this work, this approach is extended by considering a more complex surrogate model: the Wavelet Neural Network (WNN), a combination of the feed-forward neural network architecture with the wavelet transform. The WNN is used in order to obtain an expedite and accurate computational tool for the analysis and design of mooring systems. This tool should be able to replace expensive FE-based nonlinear dynamic analyses, providing nearly as good results, and with dramatic reductions in processing time, besides achieving higher accuracy than a feed-forward neural network.

The remainder of this paper is organized as follows: Initially, Section 2 presents an overview of the main characteristics of the wavelet neural networks. Next, Section 3 describes the experimental setup, including several aspects related to the data used in this research and the implementation of the WNN-based surrogate models. Then, Section 4 presents the results of the experiments, and final remarks and conclusions are presented in Section 5.

2. WAVELET NEURAL NETWORKS

In the last years, the interest for computational intelligence methods for time series prediction increased considerably. Among them are the wavelet neural networks, whose representations are based in the wavelet transform.

In the first half of the nineties, several researches about synthesis and application of wavelet neural networks were published (Zhang and Benveniste, 1992; Pati and Krishnaprasad, 1993; Zhang, *et al.*, 1995). More recently, Zhang *et al*. (2001) reported results from the application of wavelets for time series prediction. The wavelet transform also was used by Soltani (2002) for non-linear time series prediction, and Chen *et al*. (1999) applied a wavelet neural network for chaotic time series prediction. This section provides an introduction to wavelet functions and wavelet neural networks.

2.1 Wavelet functions

The origin of the concept of wavelet is in the beginning of the last century, as an extension of the Fourier transform. However, the real application of the concept only started many decades after, in the eighties. Later, it was verified that the concept of wavelet could provide an efficient tool for signal processing, sound and image compression, etc. Besides, the wavelet transform approach is a powerful tool for the approximation of functions and it became very popular in statistical analysis of time series (Nason and Sachs, 1999).

Wavelets are finite-energy functions with localization properties that can be used very efficiently to represent transient signals, that is, only a small finite number of coefficients is needed to represent a complex signal (Chan and Liu, 1998). In contrast with sinusoidal functions of infinite extent, the area under the graph of the wavelet $h(t)$ is zero:

$$\int_{-\infty}^{\infty} h(t)dt = 0 \qquad (1)$$

The first continuous wavelet function developed was the Morlet wavelet (Goupillaud, *et al.*, 1985). This wavelet is very efficient for the detection of oriented features in the signal, that is, regions where the amplitude is regular along one direction and has a sharp variation along the perpendicular direction (Antoine, 2004). The Morlet wavelet already was used for time series, such as audio signals or seismic data (Bijaoui, 2004).

Many other wavelet functions were proposed since then. Twelve wavelet functions were used in this research. They are listed in Tab. 1. Only continuous wavelet functions were used, because their parameters can be considered as coefficients of an artificial neural network, and can be learned by means of the gradient descent technique (Oussar and Dreyfus, 2000)

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Table 1. Wavelet functions

Wavelet	Formula
Morlet	$\cos(\varpi_0 \tau)\exp\left(-\frac{\tau^2}{2}\right)$
RASP1	$\frac{\tau}{\left(\tau^2+1\right)^2}$
RASP2	$\frac{\tau\cos(\tau)}{\tau^2+1}$
RASP3	$\frac{\sin(\pi\tau)}{\tau^2-1}$
SLOG1	$\frac{1}{1+e^{-\tau+1}}-\frac{1}{1+e^{-\tau+3}}-\frac{1}{1+e^{-\tau-3}}+\frac{1}{1+e^{-\tau-1}}$
SLOG2	$\frac{3}{1+e^{-\tau-1}}-\frac{3}{1+e^{-\tau+1}}-\frac{1}{1+e^{-\tau-3}}+\frac{1}{1+e^{-\tau+3}}$
POLYWOG1	$\tau\exp\left(-\frac{\tau^2}{2}\right)$
POLYWOG2	$\left(\tau^3-3\tau\right)\exp\left(-\frac{\tau^2}{2}\right)$
POLYWOG3	$\left(\tau^4-6\tau^2+3\right)\exp\left(-\frac{\tau^2}{2}\right)$
POLYWOG4	$\left(1-\tau^2\right)\exp\left(-\frac{\tau^2}{2}\right)$
POLYWOG5	$\left(3\tau^2-\tau^4\right)\exp\left(-\frac{\tau^2}{2}\right)$
Shannon	$\frac{\sin(2\pi\tau)-\sin(\pi\tau)}{\pi\tau}$

Note that the energy of the wavelet is concentrated in a certain region. This localization property is an important feature of the wavelets. If a wavelet is more localized (that is, the energy of the wavelet is concentrated in a smaller region), it produces a better representation of the signal, achieving higher resolution and requiring less coefficients in the representation.

For a given wavelet $h(t)$, a scaled and translated version is given by:

$$h_{a,b}(t)=\frac{1}{\sqrt{a}}\cdot h(\tau), \quad \text{where} \quad \tau=\frac{t-b}{a} \tag{2}$$

The parameter a corresponds to the scale, whereas b is the translation parameter. The wavelet $h_{1,0}(t) = h(t)$ is called mother wavelet.

It is important to note that the shape of the wavelet remains the same under translation and scaling. Wavelet signal processing seeks to decompose a transient signal into a linear combination of scaled and translated versions of the mother wavelet, called daughter wavelets (Lekutai, 1997).

2.2 Wavelet neural networks

A combination of the feed-forward neural network architecture with the wavelet transform has been considered as an alternative for the approximation of non-linear functions. This combination resulted in the algorithm called wavelet neural network, or wavenet (Ferrari, *et al.*, 2006).

A wavelet neural network is an artificial neural network which uses daughter wavelet functions as activation in the neurons of the hidden layer. The structure of a wavelet neural network can be seen in Fig. 1.

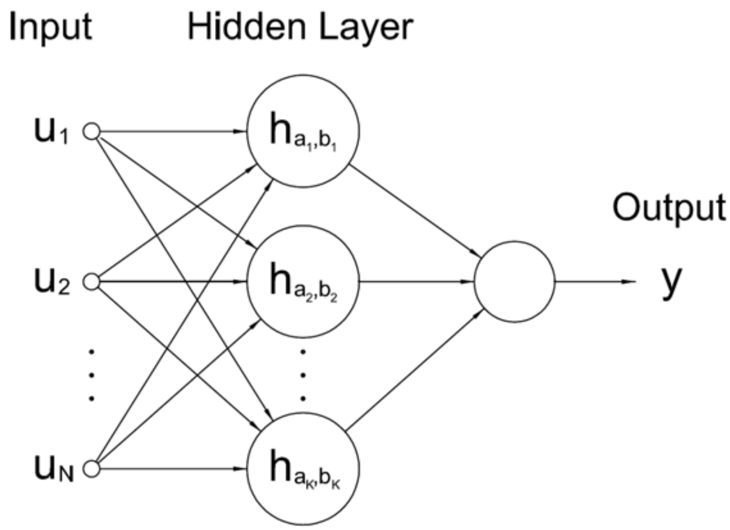

Figure 1. Wavelet neural network structure

The wavelet neural network algorithm consists of adjusting the scale and translation vectors and synaptic weights in order to minimize the error.

The network output can be represented by Eq. (3), where $u_i(t)$ is the *i-th* network input, $i = 1, ..., N$; J is the number of neurons in the hidden layer, also known as wavelet windows or wavelons; w_{ij} is the weight between the input i and the wavelon j; w_j is the weight between the wavelon j and the output; and $h_{a_j,b_j}(.)$ is the translated and scaled daughter wavelet function for the wavelon j.

$$y(t) = \sum_{j=1}^{J} w_j h_{a_j,b_j}(\sum_{i=1}^{N} w_{ij} u_i(t)) \tag{3}$$

The error can be minimized by means of the cost function shown in Eq. (4).

$$E = \frac{1}{2} \cdot e^2(t) \tag{4}$$

where $e(t)$ is the error given by the difference between the expected output and the network output, and T is the maximum number of training points.

Minimization of Eq. (4) requires calculation of the gradient vector:

$$\left(\frac{\partial E}{\partial a_j}, \frac{\partial E}{\partial b_j}, \frac{\partial E}{\partial w_j} \right) \tag{5}$$

By analyzing Eq. (2) and (3):

$$\frac{\partial E}{\partial w_j} = e(t) h'(\tau_j) \tag{6}$$

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$$\frac{\partial E}{\partial b_j} = -e(t) w_j \left(\frac{1}{a_j} \right) h'(\tau_j) \tag{7}$$

$$\frac{\partial E}{\partial a_j} = -e(t) w_j \left(\frac{1}{a_j} \right) \tau_j h'(\tau_j) = \tau_j \frac{\partial E}{\partial b_j} \tag{8}$$

Let η_a, η_b and η_w be the learning rate values corresponding to the parameters *a*, *b*, *w*. In each epoch, the synaptic weights, scale and translation vectors can be updated by means of Eq. (9), (10), (11):

$$w_j^{t+1} = w_j^t + \eta_w \Delta w_j^t \ , \quad \text{where} \quad \Delta w_j = \frac{\partial E}{\partial w_j} \tag{9}$$

$$a_j^{t+1} = a_j^t + \eta_a \Delta a_j^t \ , \quad \text{where} \quad \Delta a_j = \frac{\partial E}{\partial a_j} \tag{10}$$

$$b_j^{t+1} = b_j^t + \eta_b \Delta b_j^t \ , \quad \text{where} \quad \Delta b_j = \frac{\partial E}{\partial b_j} \tag{11}$$

3. EXPERIMENTAL SETUP

The surrogate models described in this work are applied to estimate the time series of top tensions for a mooring line from a typical floating production system, similar to the employed in deep waters in the Campos Basin, Southeastern Brazil. The platform, installed at a water depth of 2000m, is moored by 16 lines in a conventional catenary configuration. Fig. 2 shows a top view of the platform with its mooring lines and risers.

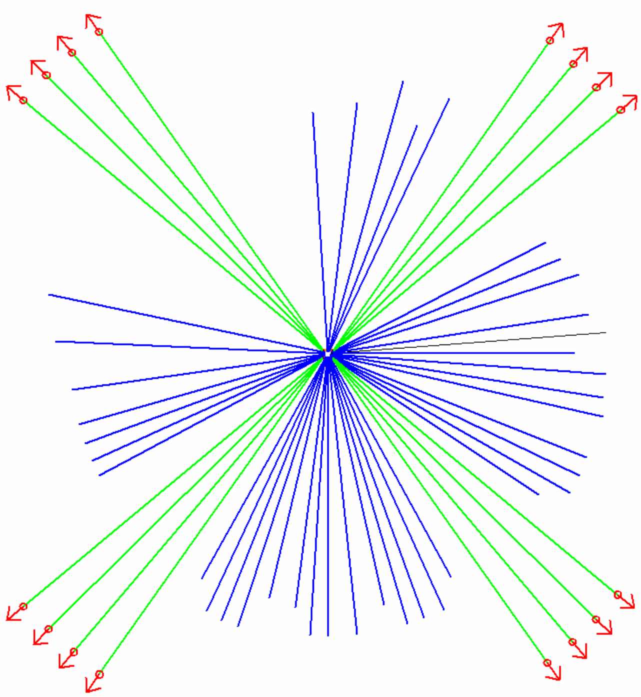

Figure 2. Coupled Model of the FPS, Top View

All mooring lines are comprised by an intermediate polyester segment, and by top/bottom chain segments. The properties of the mooring line segments are presented on Tab. 2. The mooring lines are discretized with truss elements, with a mesh gradation where the smaller elements are on the top and TDP segments (with element lengths of about 5m), and the intermediate suspended segment have larger elements (with lengths of about 25m). The selected mooring line corresponds to the most loaded line.

Table 2. Properties of the line segments.

Property	Mooring Lines	
	Chain	Polyester
Nominal Diameter (m)	0.167	0.201
Weight in Air (kN/m)	5.4718	0.2609
Weight in Water (kN/m)	4.7605	0.0686
EA (kN)	1672453	169821

The platform motion time series can be obtained from different analysis procedures. Here, the complete motion time-series are directly obtained in the context of a *hybrid* methodology (Senra, *et al.*, 2005), where a *coupled motion analysis* is performed with the in-house, non-commercial PROSIM program (Jacob and Masetti, 1998; Jacob, 2005). This program incorporates, in the same computer code and data structure, hydrodynamic models for the representation of the hull, coupled to a Finite Element model to represent the hydrodynamic and structural behavior of the mooring lines and risers. The "hybrid methodology" then consists in performing a "coupled motion analysis" considering a set of wave, wind and current loadings, with the mooring lines and risers modeled by a relatively coarse FE mesh: not sufficiently refined to provide the detailed structural response of the lines, but enough to obtain a better assessment of the platform motions taking into account the contribution of the lines.

The motion analysis that provides the surge, sway and heave time series are performed using the PROSIM program. For the case study considered here, the wave loads are represented by an irregular seastate defined by the JONSWAP model with the following parameters: Hs = 6.19m and Tp = 13.54s. Wind loads consider the API spectrum, with mean velocity of 13.709 knots. Current loads are represented by a triangular profile of velocities, with 1.0 m/s at the sea surface and zero at the bottom. All loads are aligned with the local y-axis of the platform. The analysis is performed for a total simulation time of 10800s, which is a standard practice for the analysis of floating production systems, using a time step $\Delta t = 0.1$s which is adequate in the context of a coupled motion analysis (Jacob, *et al.*, 2012a). Figures 3, 4 and 5 present short windows of the resulting surge, sway and heave series respectively.

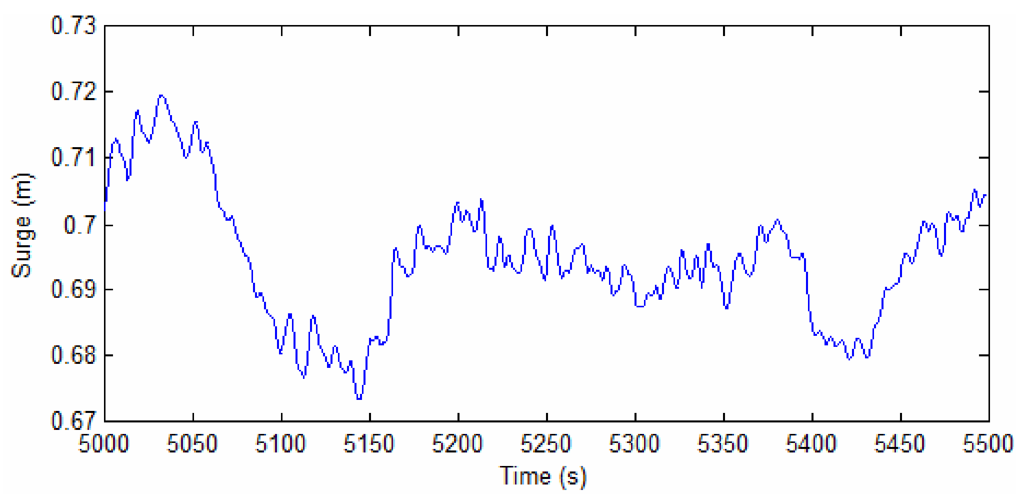

Figure 3. Window of the motion series: surge.

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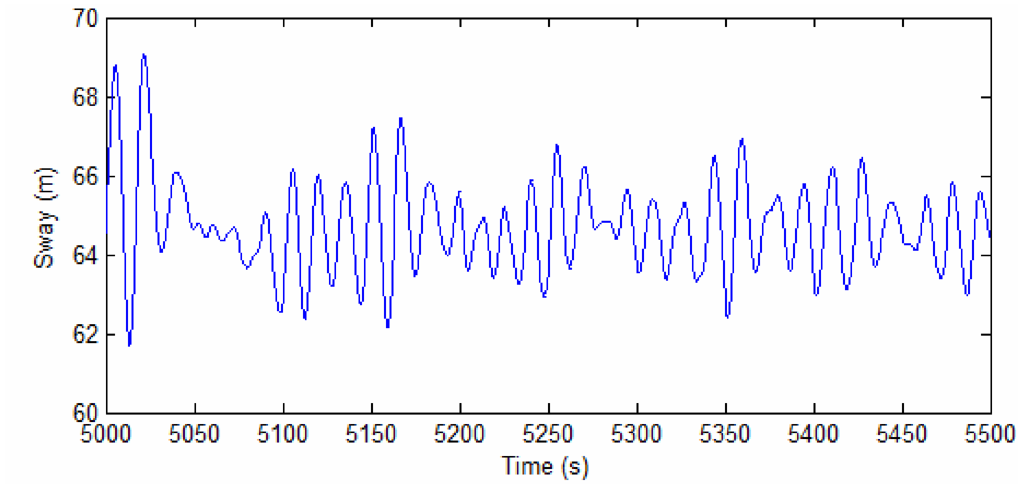

Figure 4. Window of the motion series: sway.

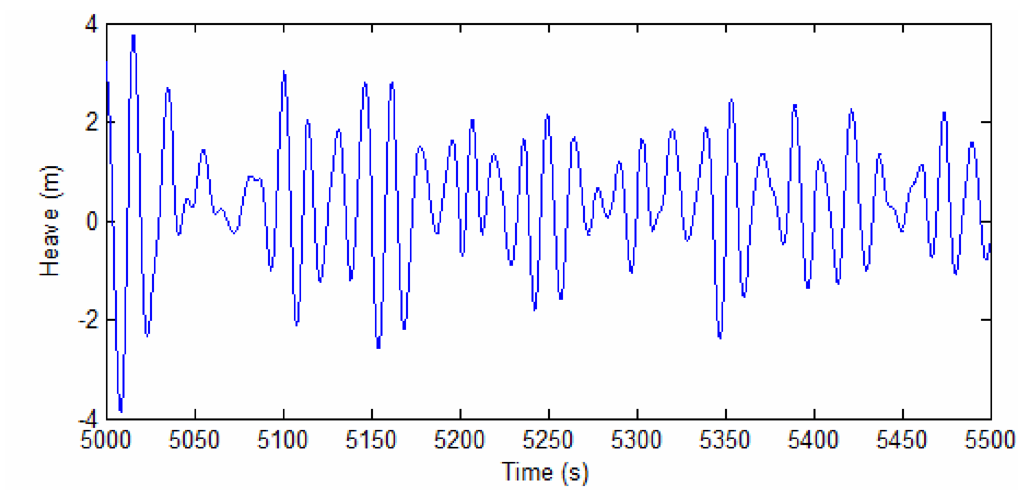

Figure 5. Window of the motion series: heave.

It is interesting to mention that the result may be anyone that could be obtained by a FE simulation (i.e. displacements and/or forces at any given node of the FE mesh), but on the remainder of the text the chosen typical result will be the top tension time series $r(t)$. The following expression summarizes the procedure for estimation of the top tension:

$$r(t) = f(\mathbf{W}, \mathbf{A}, \mathbf{B}, \mathbf{X}(t)) \tag{12}$$

In this expression $f(.,.,.,.)$ represents the particular surrogate model employed (in this case, WNN); **W** represents the set of synaptic weights; **A** represents the scale vector; **B** represents the translation vector. **W**, **A**, and **B** will be automatically adjusted during the training of the WNN); and $\mathbf{X}(t)$ is the input of the model (comprised by time-series that represent the dynamic behavior of the system). According to which time series comprise the input $\mathbf{X}(t)$ of the surrogate model, different methods can be defined to estimate the desired result.

The approach proposed in (Pina, *et al.*, 2013) is to associate an ANN with a Nonlinear AutoRegressive model with eXogenous inputs (NARX) (Nelles, 2001). Such model relates the present value of the desired time series not only to present and past values of exogenous series, but also to past values of the desired series itself. The same procedure can be applied to WNN.

Here the exogenous inputs are the motion series (surge, sway, and heave x(t), y(t), z(t)); recalling that the variable of interest is the top tension r(t), the following expression defines the inputs for the estimation of the response by the WNN-based surrogate model:

$$\begin{aligned}\mathbf{X}(t) = [&r(t-\Delta t),\dots,r(t-N_r\Delta t),\\ &x(t),x(t-\Delta t),\dots,x(t-N_x\Delta t),\\ &y(t),y(t-\Delta t),\dots,y(t-N_y\Delta t),\\ &z(t),z(t-\Delta t),\dots,z(t-N_z\Delta t)]\end{aligned} \qquad (13)$$

where N_r, N_x, N_y, N_z, and Δt are defined as before. The total number of inputs is equal to $N_x + N_y + N_z + N_r + 3$.

Although for practical applications of the surrogate models only a short initial window of the desired time series is needed for training, here the individual FE simulations for the mooring line are performed for the full 10800s in order to obtain a "test set" of FE results to be compared with the estimated results.

It is well known that the structural dynamic analysis of individual lines requires smaller time steps than those usually employed for coupled motion analyses (Jacob, *et al.*, 2012a). Therefore these FE analyses are performed with a time step value $\Delta t = 0.05$s , employing an interpolation procedure for the motion time series prescribed at the top of the lines, as described in (Correa and Jacob, 2011).

4. RESULTS

The first step in the experimental evaluation of the proposed approach was the choice of the wavelet function best suited for the wavelons in the wavelet neural network applied to the available data. The experiments showed that the wavelet which achieved the best performance among all functions tested was RASP3. The shape of the RASP3 function is shown in Fig. 6.

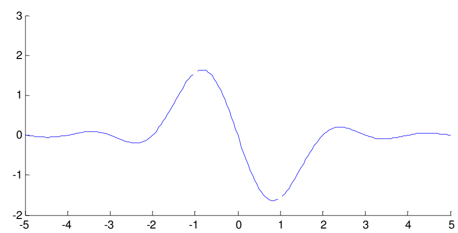

Figure 6. Shape of the RASP3 wavelet function

The next step in the experimental evaluation was the choice of the delay configuration, along with a full analysis of all other parameters, such as size of the training set, number of wavelons, etc.

Different models can be defined by varying the values of the delays N_x, N_y, N_z and N_r of Eq. (13) for each one of the input time-series. Previous experiments (Pina, *et al.*, 2013) were performed to establish adequate ranges for these values. The configurations that resulted from those experiments are presented on Tab. 3. The other parameters that must be set are: the sizes of the training and validation sets, the number of wavelons in the hidden layer, the learning rate, and the maximum number of epochs. For each configuration, 20 independent runs were performed, and the results are statistically consolidated.

The parametric analysis showed that the use of models with $N_r = 5$ for the delay of the top tension time series provided the best results. Further, among all tested configurations for the other parameters, the one that achieved best results was with a training set of 1000 points (500s), without using a validation set, 15 wavelons in the hidden layer, learning rate of 0.01, and maximum number of epochs equals to 700.

The use of a validation set affects the learning task, stopping training before an optimal point. This is due to the fact that the wavelet neural network has two self-adjusting parameter vectors in addition to the synaptic weights, so that the training error is not monotonically decreasing. The risk of overfitting is minimized by the choice of an appropriate size for the training set. The gain in running time provided by early stoping does not compensate the loss in accuracy. It could be observed that 15 wavelons in the hidden layer are sufficient to obtain good results, and more than that can affect accuracy, besides causing a slower training. A very small value for the learning rate seems to be the appropriate choice. Higher learning rates can hamper convergence, mainly because of the setting of the scale and translation parameters. Table 3 summarizes the results achieved by each model for the parameter settings mentioned.

Since it was verified that the use of early stopping could damage the performance of the models in terms of accuracy, the running time is closely related to the number of inputs, determined by the delays. This can be confirmed by analyzing the last column of Tab. 3, that presents the average CPU time needed to train the wavelet neural network and to predict the top tension values for the test set.

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Table 3. Results of the experiments.

Configuration				Training Error (mse)		Test Error (mse)		CPU Time (s)
N_x	N_y	N_z	N_r	μ	σ	μ	σ	
10	10	10	5	1.24 e-05	3.13 e-06	3.57 e-05	2.18 e-05	269.92
10	10	15	5	1.36 e-05	4.45 e-07	2.48 e-05	8.87 e-06	277.72
10	10	20	5	1.52 e-05	5.74 e-06	2.31 e-05	5.28 e-06	286.53
15	15	15	5	1.07 e-05	3.60 e-06	2.48 e-05	7.65 e-06	289.65
15	15	20	5	8.94 e-05	1.02 e-04	5.02 e-05	1.85 e-05	298.00
20	20	20	5	1.90 e-05	1.06 e-05	3.16 e-05	1.17 e-05	312.86
10	10	10	10	1.04 e-05	2.18 e-06	4.01 e-05	9.83 e-06	275.03
10	10	15	10	3.11 e-05	1.77 e-05	4.46 e-05	9.12 e-06	286.44
10	10	20	10	4.29 e-05	4.32 e-05	4.01 e-05	6.18 e-06	294.87
15	15	15	10	1.94 e-05	9.03 e-06	4.24 e-05	1.81 e-05	298.31
15	15	20	10	3.27 e-05	2.43 e-05	6.39 e-05	1.65 e-05	309.12
20	20	20	10	2.86 e-05	2.30 e-05	5.35 e-05	4.09 e-05	320.71

The accuracy is measured by the training error and test error (prediction error), consolidated in terms of mean μ and standard deviation σ over the 20 runs for each configuration. The test errors of Tab. 3 for each model are graphically represented on Fig. 7, in terms of their confidence interval (with lower and upper limits defined as $\mu - \sigma$ and $\mu + \sigma$ respectively). It can be observed that $N_r = 5$ configurations present noticeably better accuracy than the $N_r = 10$ configurations. Further, the configuration $N_x = 10$, $N_y = 10$, $N_z = 20$, $N_r = 5$ achieved the best overall performance. Figure 8 presents a window of the estimated top tension time series for the mooring line, compared with the actual results from the FE analysis. Note how close are the predictions achieved by the model.

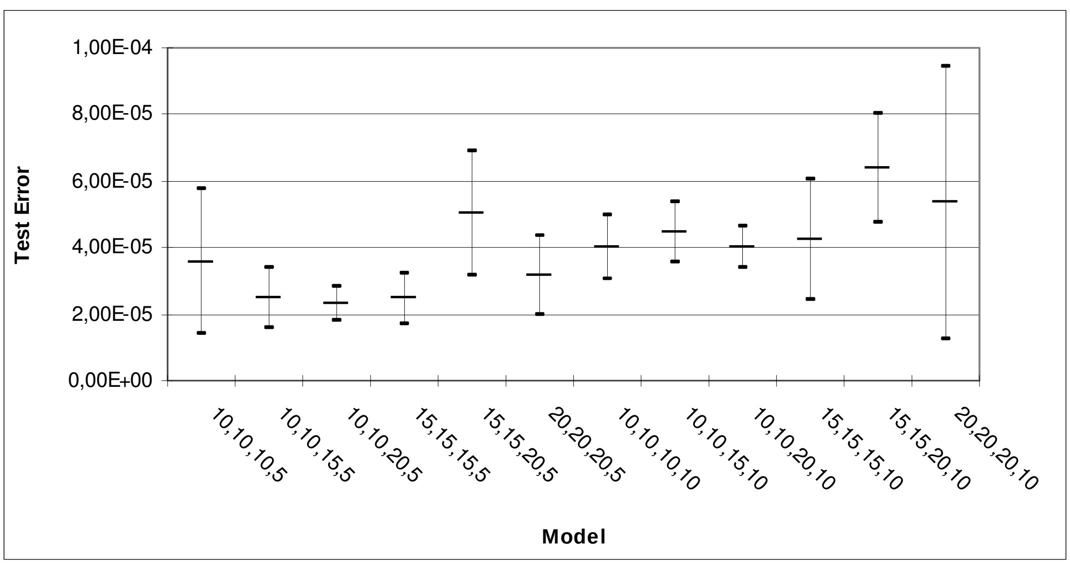

Figure 7. Accuracy of the WNN-based surrogate models

One important result of this research is to show that the wavelet neural network can be more adequate for this problem than a simple feedforward neural network. Figure 9 shows the test error comparison. Note that the wavelet neural network performs better than a simple feedforward artificial neural network trained with the same configuration. Besides, these results are much better than those presented in (Pina, *et al.*, 2013), which uses typical values for the parameters. This suggests that an extensive parameter analysis is essential to find the best model to be applied.

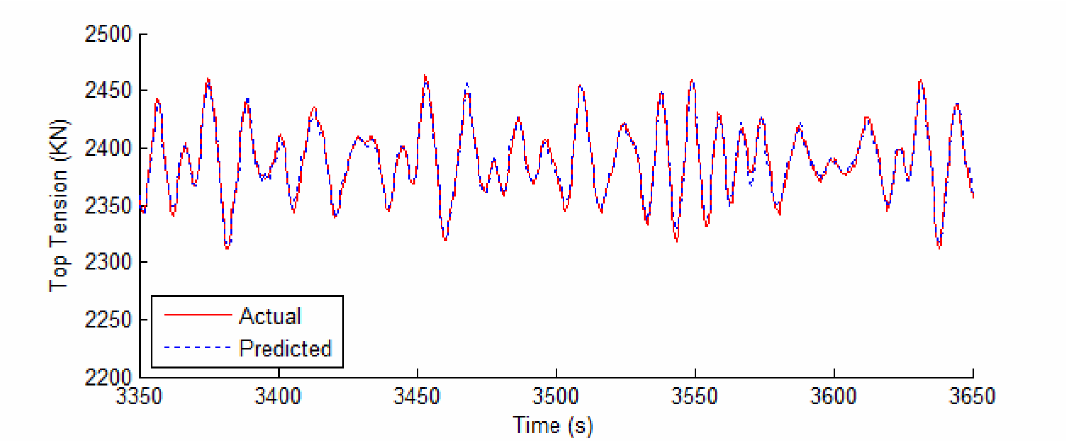

Figure 8. Predictions provided by the best configured model of WNN

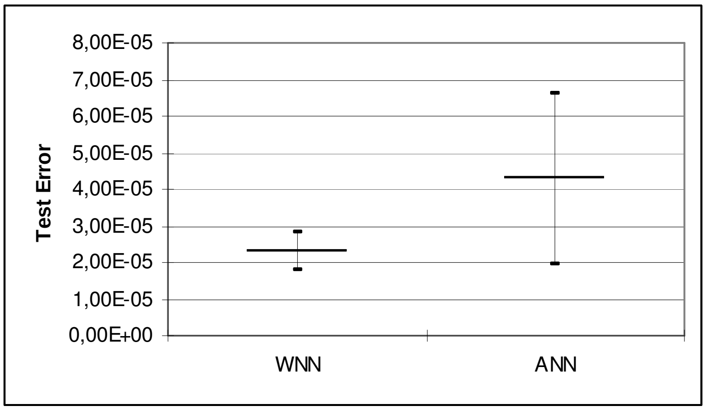

Figure 9. Comparison between WNN and ANN

5. CONCLUSION

This work presented results to support the application of wavelet neural networks as surrogate models, in order to replace nonlinear dynamic analyses with finite elements, providing a significant speed-up in the search for optimal configurations in mooring systems.

In order to train the WNN, the procedure requires only a short FE simulation to obtain an initial window of the top tension time series of a mooring line. Therefore, this approach can be about 14 times faster than the use of a full 3-hour FE simulation.

Observing the results of the case studies, it can be verified that the surrogate models provide an adequate estimation of the desired result, with the WNN performing remarkably better than the ANN. This indicates that the WNN approach proposed in this work comprises a better alternative for practical uses on estimating the top tensions of mooring lines of FPS (or any other result that could be obtained by a FE simulation), replacing the full use of FE-based numerical tools mainly at preliminary design stages, or associated to optimization procedures by evolutionary methods.

Moreover, the parametric analysis showed that a proper configuration can achieve substantially better results than using typical values, reducing the test error in more than 80%.

These results are of high practical importance for the oil industry, since they will allow the definition of more efficient and economical configurations for mooring systems, leading to more efficient designs for such structural systems which are crucial in offshore oil exploitation.

Another aspect that can be addressed is the development of a surrogate model associated to a coupled methodology for the analysis of floating production systems (Jacob, *et al.*, 2012a). In this approach, instead of having to perform a full hydrodynamic analysis in order to obtain the motions of the platform to be prescribed at the top of a given mooring line or riser, the surrogate model would obtain simultaneously both the platform motions and the desired parameters of the response of the lines. This way, expensive coupled simulations could be avoided, again comprising a rapid computational tool to be used at preliminary design stages, or associated to optimization procedures.

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