ARTIFICIAL NEURAL NETWORKS APPLIED TO FLEXIBLE PIPES STOCHASTIC NON LINEAR DYNAMIC ANALYSIS

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Abstract. *In order to refine and optimize flexible pipes design, due the continuous increasingly challenging deep water environments, a lot of attention is put into setting up more realistic and sophisticated models for global dynamic numerical analyses. Recently, different hybrid methods combining Finite Element Analyses (FEA) and Artificial Neural Networks (ANN) have presented promising results in terms computational costs reduction when applied to the simulation of mooring lines. The hybrid ANN-FEA methodology presented in this work aim to reduce the computational costs involved in flexible pipes stochastic nonlinear global dynamic analyses, predicting flexible pipe tension and curvatures in the bend stiffener region. A typical 6''free-hanging flexible pipe was numerically simulated with the application of 88 different fatigue sea states coming from 8 directions. For each sea state, the hybrid approach is applied in this way: firstly using short FEA simulations an ANN is trained and then using only the ANN and the prescribed floater motions the rest of the response time histories are obtained. With the predicted tension and curvatures a local analysis is used to calculate stresses in tensile armour wires and the corresponding fatigue lives. To evaluate the optimal ANN configuration a sensitive analysis was developed regarding two ANN main parameters: training time series length and neurons in the hidden layer.*

Keywords: *Flexible pipes, Artificial neural networks, Stochastic dynamic analysis*

1 INTRODUCTION

The importance of flexible pipes for the oil and gas offshore industry is rapidly increasing along the last years. In order to further refine and optimize flexible pipes design in increasingly challenging deep water environments a lot of attention is put into setting up more realistic and sophisticated numerical models for time domain dynamic analyses. The combination of the need for detailed nonlinear models and the demand for long time series simulations makes the design of these types of structures very time consuming and costly.

This is the case of flexible pipe fatigue calculations, where a lot of expensive stochastic nonlinear dynamic analyses using Finite Element Analysis (FEA) are needed. As commented in (FILHO,2012), depending on the water depth, mesh discretization and criticality of the environmental conditions a single full 3-h (10800s) long riser simulation, using 3D nonlinear beam elements, can easily take 5h - 10h of computer time.

Increasing the number computers (cores) in order to reduce these computer simulation times is a possible solution for this challenge; however it can lead to extra high economical costs. In the last years different hybrid methods combining FEA with Artificial Neural Networks (ANN) have been presented as another alternative for reducing these computations time.

GUARIZE (2004) and GUARIZE *et al.* (2008) used an ANN methodology to predict the dynamic top tension response of mooring lines and obtained a reduction in the computer time by a factor of about 20 compared to conventional and full FEA nonlinear numerical analysis. CHRISTIANSEN *et al.* (2013) used a similar approach to perform a full fatigue life analysis of a mooring line connected an offshore floating unit reducing the simulation time dramatically. The fatigue life assessment using a trained ANN was two orders of magnitude faster than using the corresponding full FEA. *PINA et al.* (2013) also studied different surrogate models to predict coupled mooring and riser top tension dynamics behavior with significant reduction in computer time when compared to full FEA simulations.

The idea behind ANNs is to try to reproduce the human brain's ability to learn, recognize and predict patterns of different types. In this paper an ANN learns, recognizes and predicts the pattern of the mathematical model that relates the motions of an offshore floating unit and the dynamic load actions in a flexible pipe cross section. Of course, in order to learn this pattern, the ANN needs an example to be trained, in this case: the offshore floating unit motions are the inputs and the axial tension T and bending curvatures C_z and C_y of the flexible pipe in the bend stiffener region are the outputs. Once this pattern is learned by the ANN, as the floater motions time-series are known, the further remaining time-series of the desired responses, in this case T, C_z and C_y, are calculated using this model instead of the full FEA-based simulations.

In this paper, a hybrid ANN-FEA method is employed in order to reduce the computational costs involved with time-domain flexible pipes stochastic nonlinear FEA needed for fatigue damage assessment of this kind of slender marine structure. This paper presents a study that compares the performance of the hybrid ANN-FEA approach and the conventional full time-domain FEA-based approach for a typical 6" deep water flexible pipe. Additionally, the results from a sensitivity analysis regarding two ANN variables (training time series length and neurons in the hidden layer) are presented. Based on these results a complementary method is also proposed.

2 FLEXIBLE PIPES TENSILE ARMOURS FATIGUE ANALYSIS

Flexibles pipes are composed by a series of layers where each one has a specific functional or structural function. One example of a flexible pipe section is showed in Figure 1.

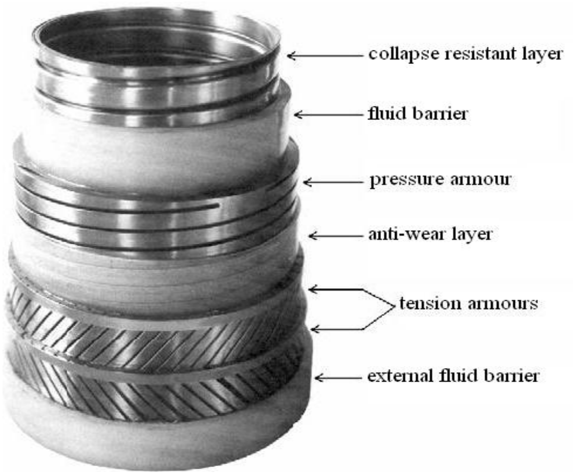

Figure 1 - Flexible pipe layers

This kind of pipe is mainly used for oil production, water or gas injection, gas export in many types of configurations: free-hanging, lazy-wave, steep-S, among others. Figure 2 shows a single free-hanging catenary flexible riser.

In the design phase of this kind of structure the global analyses are usually performed using the de-coupled methodology, where the floater motions are computed separately and imposed as prescribed top motions in the riser analysis. By applying the finite element technique (MOURELLE,1993) and (VIGNOLES,2012), the equation that describes the dynamic forces equilibrium of a flexible pipe connected to a floating production unit is given by:

$$[M]\{\ddot{X}\} + [B]\{\dot{X}\} + [K]\{X\} = \{F(t)\} \quad (1)$$

where $\{X\}$, $\{\dot{X}\}$ and $\{\ddot{X}\}$ are, respectively, the nodal displacement, velocity and acceleration vectors, $[M]$ is the inertia matrix (including structural and added masses), $[B]$ is structural the damping matrix, $[K]$ the structure´s stiffness matrix and $\{F(t)\}$ is the vector containing the nodal time-varying excitation forces applied to the riser including those from the top prescribed floater motions. The other sources of forces are the functional loads from buoyancy and dead weight and the hydrodynamic loading from waves and current acting on riser itself. The later loading is usually computed by means of Morison equation (CHAKRABARTI,1987).

In order to take into account all nonlinearities involved in the global analysis, such as soil-structure contact and large displacements, it is recommended to perform time-domain stochastic FEA-based simulations for all sea states belonging to the scatter diagrams associated to the location where the platform is placed on. From these global analyses the time-histories of axial tension $T(t)$, and bending local curvatures $C_z(t)$ and $C_y(t)$ along the riser length are obtained for each sea state.

Then, using the time traces of the axial tension $T(t)$ and the curvatures $C_z(t)$ and $C_y(t)$, a local analysis using a FEA numerical code (SOUZA,2005; CALEYRON *et al.*,2014) or analytical solutions (FERRET *et al.*,1987; FERRET *et al.*, 1995) is performed in order to estimate the stress time-series in the flexible pipe tensile armours wires. This procedure is summarized in Figure 2 for a single riser section.

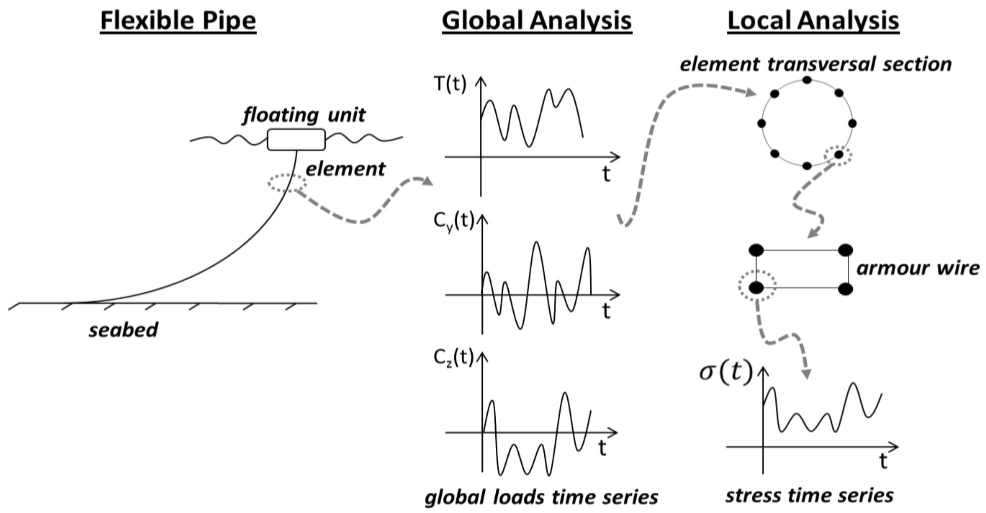

Figure 2 - Flexible pipe fatigue calculations summary

After the stress time-stories have been determined, a cycle counting method, such as Rainflow technique (ASTM,2011), is applied in order to count the cycles and their corresponding stress ranges for fatigue damage assessment. The fatigue damage in the flexible pipe tensile armours is usually computed by means of S-N curves and Miner-Palmgren cumulative damage rule (MINER,1945). According to this rule, the fatigue damage is expressed as:

$$D = \sum_{j=1}^{N_{ss}} \sum_{i=1}^{N_c{}^j} \frac{n_i^j}{N(S_i)} \gamma_j \tag{2}$$

where $N_c{}^j$ is the number of stress ranges identified in j^{th} sea state, N_{ss} is the total number of sea states considered in fatigue analysis (considering the scatter diagrams for all wave directions), n_i^j is the number of identified stress cycles with stress range S_i, $N(S_i) = K(S_i)^{-m}$ is the allowable number of stress cycles given by the S-N curve, K and m are the S-N curve parameters and γ_i is the relative frequency of occurrence for each j^{th} sea state. The fatigue failure is assumed to occur whenever the fatigue damage D is equal or greater than unity. In this paper the study is focused only in a riser section located inside the bending stiffener situated at the top riser connection. The global analyses are performed with the software Deeplines™ (PRINCIPIA, 2011) and the local analysis with an analytical solution based on FERRET *et al.* (1987) and FERRET *et al.* (1995), and coded by VIGNOLES (2002).

It is important to notice that for fatigue analysis of flexible pipes the number of sea states can be very large and the most time consuming part of this analysis is related to the global riser analyses. These analyses must be long enough in order to minimize the uncertainties in fatigue damage estimations. The methodology described in what follows focus on reducing the computer time of the global riser analyses by using a hybrid methodology based on Artificial Neural Networks.

3 ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks can be explained by different ways: biologically, based on learning theories and also mathematically. This paper will focus on its mathematical definition.

One of many abilities of the ANNs is their power to approximate, with a certain error, any mathematical function. In theory, an ANN can represent any kind of mathematical function, even functions with some high degrees of nonlinearities. ANNs are also applied in many others applications, such as: pattern recognition, classification, clustering, time series forecasting, optimization, signal processing, among others (HAYKIN,2011).

In the following, an ANN will be trained, using a short simulation length, to recognize the mathematical relationship between the motions of an offshore floating unit and the respective flexible pipe load actions including the axial tension $T(t)$ and the bending curvatures $C_z(t)$ and $C_y(t)$ at a point inside the bending stiffener region. Once the ANN is established, it is used to predict longer time series of the load actions to be employed in the fatigue analysis.

All developments regarding Artificial Neural Networks methodology used on this work were developed using Neural Networks Toolbox™ available in Matlab™ (MATHWORKS,2012).

3.1 ANN Architecture

The basic architecture of an ANN is made by three layers: input layer, hidden layer and an output layer. For each layer there are the respective neurons. Each connection between two neurons, always in neighboring layers, contains the connection weights. This basic architecture is summarized in **Erro! Fonte de referência não encontrada.** The first neuron, for instance in the hidden layer, receives an input z given by:

$$z_j = \sum_{i=1}^{N} x_i \, w_{I_i}^{1} + b_1 \tag{3}$$

where N is the number of entrees in the input layer, x_i are inputs themselves, $w_{I_i}^1$ are the input connection weights, b_1 is a bias parameter for the input layer and $j = 1,2,3 \ldots M$, where M is the number of neurons in the hidden layer. Each neuron in the hidden layer delivers an output y_j given by:

$$y_j = \varphi_H(z_j) = \varphi_H\left(\sum_{i=1}^{N} x_i \, w_{I_i}^{j} + b_1\right) \tag{4}$$

where $\varphi_H(.)$ is the so-called activation function used in the hidden layer. Finally, for an ANN with a single output neuron, the output result is given by:

$$R = \varphi_O\left(\sum_{k=1}^{M} y_k \, w_{O_k} + b_2\right) \tag{5}$$

where R is the ANN output, $\varphi_o(.)$ is the activation function used in the output layer and the other parameters have similar definition to those of Eq. (3).

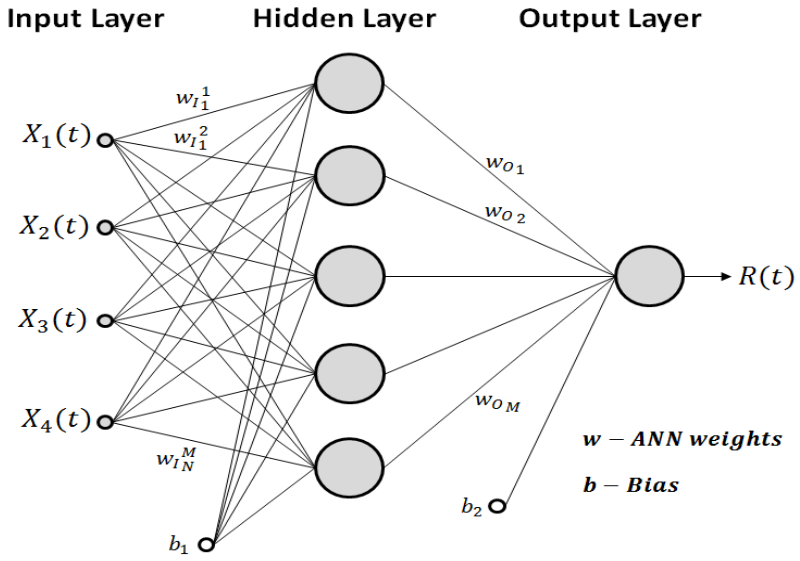

Figure 3 – ANN architecture

3.2 Training and Validation

Considering that the input and output are time-dependent variables, the input-output relationship described above associated to any ANN architecture can be generically written as the following function:

$$R(t) = f(\boldsymbol{W}, \boldsymbol{x}(t), \boldsymbol{b}) \tag{6}$$

where $\mathbf{x}(t)$ is the vector containing all inputs, $\mathbf{W}$ is a matrix containing all ANN connection weights and $\mathbf{b}$ is the vector containing the ANN biases (usually each $\mathbf{b}$ component is set equal to unity).

The training of an ANN consists in obtaining the optimal matrix $\mathbf{W}$ for a given application considering a given architecture. This is obtained by using a known set input and output values of size N. By denoting the known set of output values as $v(t)$, the matrix $\mathbf{W}$ can be obtained by solving an optimization problem aiming at minimizing the mean square error E defined as:

$$E = \frac{1}{N}\sum_{t=1}^{N}(R(t) - v(t))^2 = \frac{1}{N}\sum_{t=1}^{N}(\{\boldsymbol{W}, \boldsymbol{x}(t), \boldsymbol{b}\} - v(t))^2 \tag{7}$$

Usually an iterative optimization is used to obtain the optimum matrix $\mathbf{W}$. For each iteration the error E is evaluated. If the ANN is not trained enough, i.e., the iterative process is stopped after a limited number of iterations, high prediction errors can arise. On the other hand, if the ANN is over trained it adapts too much to the training data set, causing the so-called “over fitting”, and the prediction errors may also be high for predictions using non-trained data (HAYKIN, 2012; MURRAY, 1993). Thus, there is an optimal level of training to be found. The strategy adopted to find this optimal level is to separate part of the available data for training and other part for validation. The training process stops when the prediction error for the validation set starts to increase (MURRAY,1993).

3.3 ANN Model

The ANN is used in this work as a surrogate model for the very expensive computer simulations used in the global flexible pipe analysis at a point inside the bending stiffener. The main idea is to develop three independent ANNs to predict longer time series simulations of the axial tension $T(t)$ and the curvatures $C_z(t)$ and $C_y(t)$ as:

$$T(t) = f_T(\boldsymbol{W}_T, \boldsymbol{x}(t), \boldsymbol{b}); C_z(t) = f_{C_z}\left(\boldsymbol{W}_{C_z}, \boldsymbol{x}(t), \boldsymbol{b}\right); C_y(t) = f_{C_y}(\boldsymbol{W}_{C_y}, \boldsymbol{x}(t), \boldsymbol{b}) \tag{8}$$

where $\mathbf{W}_\mathrm{T}$, $\mathbf{W}_{\mathrm{C_z}}$ and $\mathbf{W}_{\mathrm{C_y}}$are the optimal weights obtained during the ANN training phase for the three loads actions at the riser section, $\mathbf{x}(\mathrm{t})$ is a vector containing the previously known floating unit translational and rotational motions time series.

Particularly for the case of dynamic systems with memory, as the present case, there are many ANN models available in the literature (PINA *et al.*, 2013), such as: auto regressive (AR), exogenous input (EX) and the nonlinear auto regressive network with exogenous inputs (NARX) ANN models. In this paper the latter model was employed.

In the NARX ANN model, present and past values of inputs and the past values of the outputs are all considered as input values to compute the present value of the output. Considering that, the time series are discretized at equal time steps with length $\Delta\mathrm{t}$, this model can be defined for the present application as:

$$\begin{aligned}R(t) = f[&\{x(t), x(t-\Delta t), \dots, x(t-N_x\Delta t)\}, \{y(t), y(t-\Delta t), \dots, y\left(t-N_y\Delta t\right)\}, \{z(t), z(t-\Delta t), \dots, z(t-N_z\Delta t)\}, \\ &\{\alpha(t), \alpha(t-\Delta t), \dots, \alpha(t-N_\alpha\Delta t)\}, \left\{\beta(t), \beta(t-\Delta t), \dots, \beta\left(t-N_\beta\Delta t\right)\right\}, \{\gamma(t), \gamma(t-\Delta t), \dots, \gamma\left(t-N_\gamma\Delta t\right)\}; \\ &\{R(t-\varDelta t), \dots, R(t-N_R\varDelta t)\}]\end{aligned} \tag{9}$$

where $\mathrm{R(t)}$ represents either $\mathrm{T(t)}$ or $\mathrm{C_z(t)}$ or $\mathrm{C_y(t)}$, $\mathrm{x(t)}$, $\mathrm{y(t)}$ and $\mathrm{z(t)}$ are the floater surge, sway and heave motions time series, $\alpha(\mathrm{t})$, $\beta(\mathrm{t})$ and $\gamma(\mathrm{t})$ are the floater roll, pitch and yaw motions time series, $\mathrm{N_x}, \mathrm{N_y}, \mathrm{N_z}, \mathrm{N_\alpha}, \mathrm{N_\beta}$ and $\mathrm{N_\gamma}$ are the number of time steps delays for the six floater motions and $\mathrm{N_R}$ is the number of time step delays for the response itself. These delays are needed in order take into account the memory effects in the dynamic response. The NARX ANN model is schematically shown in **Erro! Fonte de referência não encontrada.**. Coming back to Eq. (8), in a NARX ANN vector $\mathbf{x}(\mathrm{t})$ includes also some past results of the output.

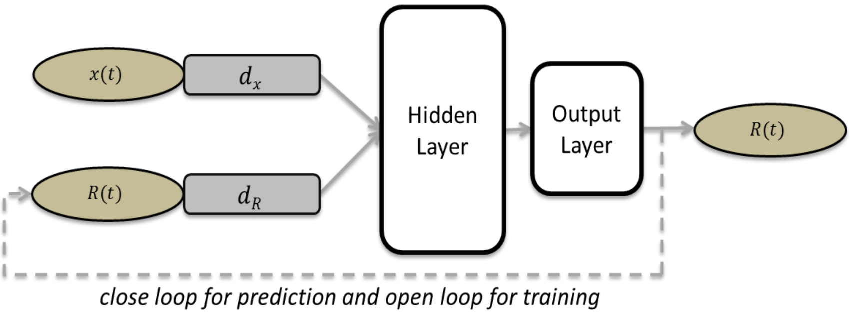

Figure 4 – Simplified sketch of the NARX ANN architecture

4 HYBRID ANN-FEA METHODOLOGY

The great advantage of a hybrid ANN-FEA method is that it joins the best features from both ANN and FEA methods, keeping a fair compromise between model sophistication and required computational costs. The idea here is to combine ANN and FEA in a proper way to maintain all features of a refined FEA model but perform time domain simulations more efficiently in terms of computer time in order to speed up global flexible riser analyses.

Based in the ANN architecture described before, the first step to perform the proposed hybrid methodologies is to train the ANN with data associated to problem under consideration. To get this data set, a short length FEA simulation is performed in order to obtain the 6 floater motions and the respective tension and curvatures, forming the called training data set. Once the FEA is ended, the obtained data set is presented to the ANN and then it is trained. When the ANN achieves its optimal weights, the training is stopped. This trained the ANN is ready to perform predictions for new input data, in this case the 6 floater motions. This new floater motions dataset is obtained separately by simulation of the floater hull motions. This simulation is usually very fast and can provide as long as wanted floater motions time series. Then this long length 6 floater motions time series are presented to the network in order to obtain the flexible pipe action loads, this time without the use of the FEA, using just the ANN. This procedure is illustrated in Figure 5.

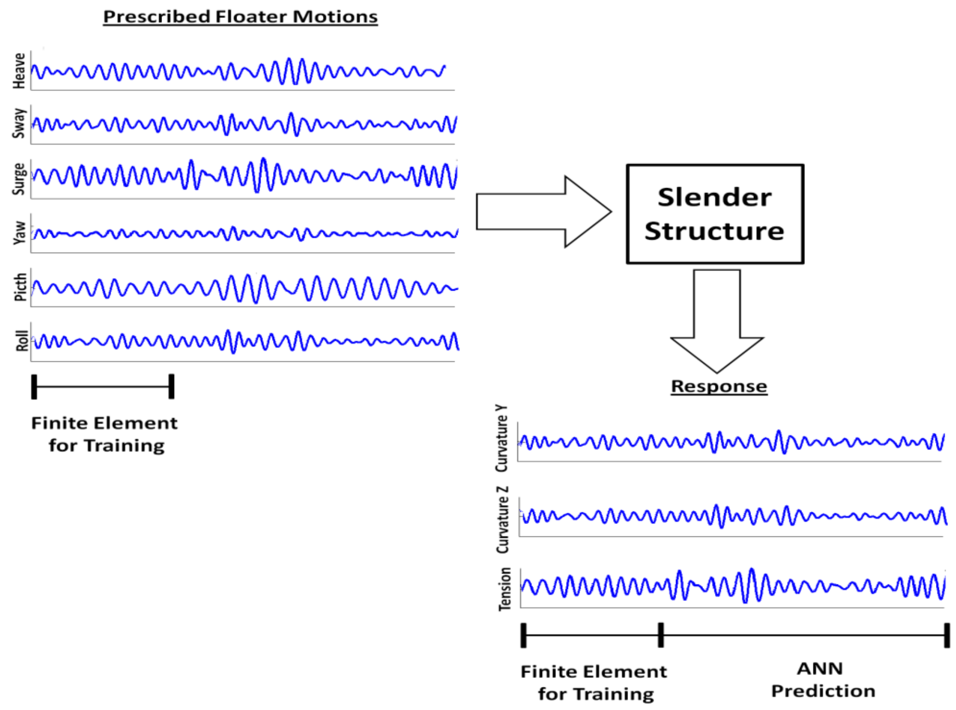

Figure 5 – Hybrid methodology for flexible pipe load actions prediction.

In the present work the hybrid methodology is applied individually to obtain the load actions $T(t)$, $C_z(t)$ and $C_y(t)$ (described above) in 88 sea states (11 for each incidence direction) of the scatter diagram used to compute the fatigue damage of the tensile armours at the top of a 6” free-hanging flexible riser connected to a spread-moored FPSO.

5 CASE STUDY

The hybrid ANN-FEA methodology described before is employed to perform a simplified fatigue damage assessment of the tensile armours at a section inside the bending stiffener of an 6” free-hanging flexible pipe (see Figure 2) connected to a spread-moored FPSO in 2140m water depth. The simplification is concerned with wave environment description adopted (wave scatter diagram). In the present work it was used eleven sea states shown in Figure 6 for each wave direction, with their occurrence frequencies varying from one direction to another.

Directions
N - E - NE - SE - W - N - W - S - SW

Hs/Tz	3,50	3,75	4,00	4,25	4,50	4,75	5,00	5,25	5,50	5,75	6,00	6,25	6,50	6,75	7,00	7,25	7,50	7,75	8,00	8,25	8,50	8,75	9,00	9,25	9,50	9,75	10,00
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Figure 6 – Wave scatter diagram used in the simulations

In order to compare the accuracy of the hybrid ANN-FEA methodology, a 4000-s long stochastic time domain global riser analysis was performed for each sea state using Deeplines^{TM} software (PRINCIPIA,2012). The sea surface elevation in all sea states was modeled by means of the JONSWAP spectrum (FALTINSEN,1993). Afterwards, the corresponding local analyses were performed using the analytical model based on FERRET *et al.* (1987), FERRET *et al.* (1995) and VIGNOLES (2002) and the fatigue damage assessment was performed using Rainflow cycle counting method (ASTM,2011) and Miner´s rule with a S-N curve with parameters logK=15.01 and m=4 (NAESS,1999).

5.1 ANN Architecture and Training Details

After some initial tests and also based on GUARIZE (2004), GUARIZE *et al.* (2008), PINA *et al.* (2013) and CHAVES *et al.* (2015) a number of 10 neurons was selected for the hidden layer and 500s long time series of the floater motions and responses were taken for training (400s) and validation (100s) of the NARX ANN for the load effect T. The NARX ANNs for the load effects C_z and C_y attained the best training with 15 neurons in hidden layer. The number of delays adopted in all ANNs for all variables was equal to 10 and the time series have been sampled with a time step of 0.2s. Beside these details, the following settings in the Matlab Neural Networks Toolbox (MATHWORKS, 2012) were also adopted:

- Optimization algorithm: Levenberg-Marquadt method
- Weights initialization: the Nguyen-Widrow algorithm
- Default normalization of inputs and outputs were employed

5.2 Sensitivity Analysis

The sensitivity analysis is an important phase when the ANN is applied to a physical problem. This sensitivity study can be applied to different variables involved in ANN architecture. In order to evaluate if the variables values selected in Item 5.1 are the optimal, in terms of ANN performance, a sensitivity analysis was performed regarding two main ANN variables:

- Training time series length
- Number of neurons on hidden layer

A set of sea states, from different directions, was selected to be part of the sensitivity study according to Table 1.

Table 1-Sea states selection

Index	Hs(m)	Tz(s)
E3	1.25	5.25
NE6	2.75	7.25
S1	0.25	3.75

This sensitivity analysis was applied for the three networks, ANNs for T, Cy and Cz. Other variables, such as inputs delay, were not considered in this sensitivity study.

The sensitivity variability is evaluated by means of root of the mean square error, described by Eq. 7, from a short length of the prediction data set. Figures 7 to 9 shows these results as function of the number of neurons on the hidden layer and Figures 10 to 12 shows the corresponding results as function of the training time series length.

Based on the results presented in these figures it can be observed that:

- The optimal value for both parameters varies according to each sea state for both number of neurons in the hidden layer and training time series length. This behavior is more evident for the number of neurons in the hidden layer.
- Regarding the number of neurons in hidden layer, the tendency is that, after finding the optimal value, the performance starts to decrease.

Based on these findings two approaches were used in this work concerning the number of neurons used in the hidden layer, which are:

- Method A – uses the fixed number of neurons in the hidden layer described in the item 5.1 for all sea states.
- Method B – the number of neurons in the hidden layer varies for each sea state. The exact number of neurons is determined by the best performance during the ANN training. This method is proposed since each sea state has its own complexity and consequently needs a specific number of neurons.

The training time series length adopted for all cases was 400s and validation length was 100s. So, the initial FEM analysis for every sea state is 500s.

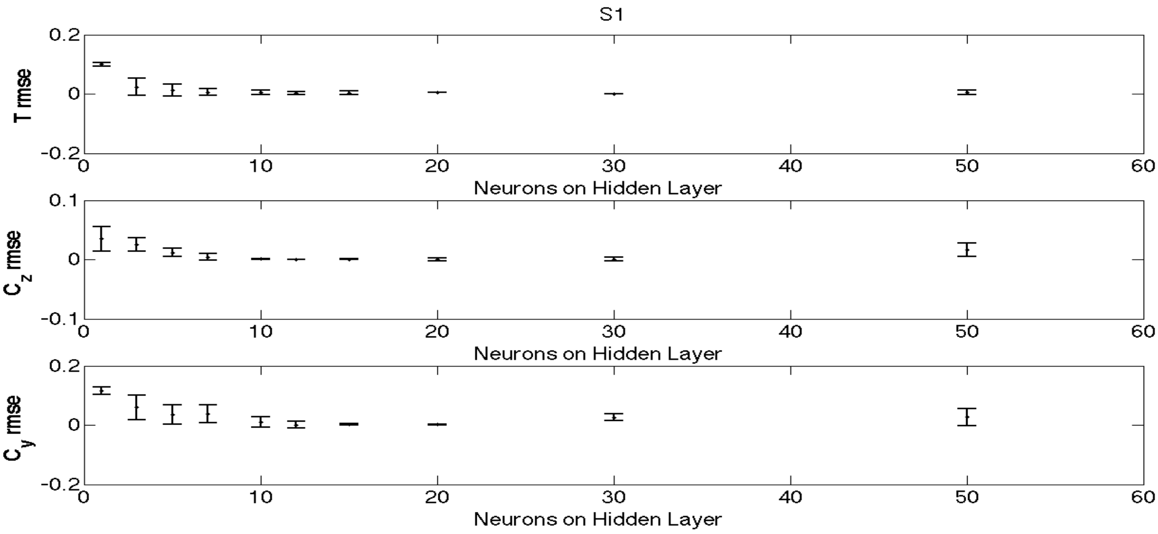

Figure 7-Number of neurons on hidden layer sensitivity analysis (sea state S1)

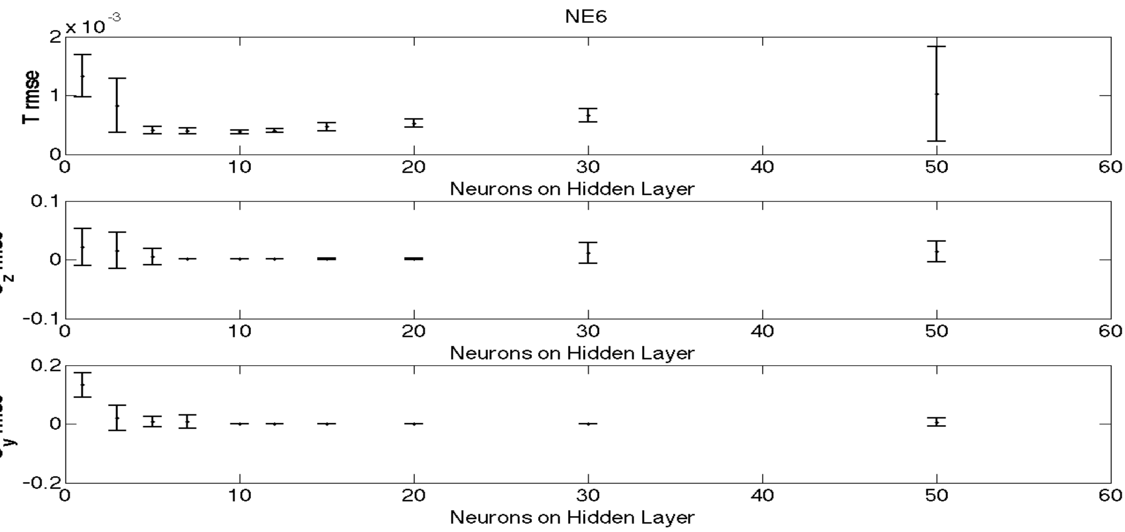

Figure 8-Number of neurons on hidden layer sensitivity analysis (sea state NE6)

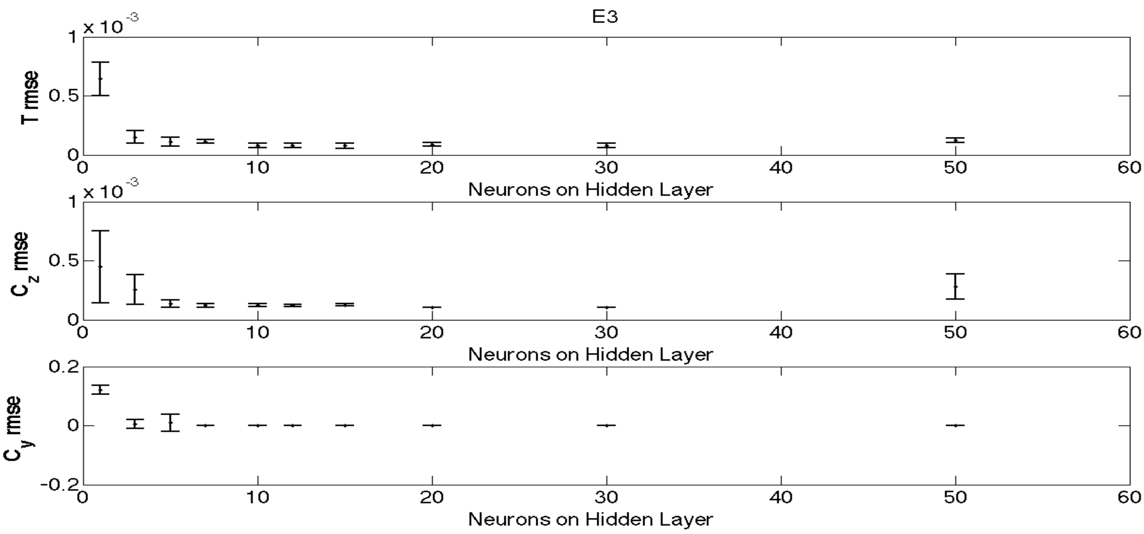

Figure 9-Number of neurons on hidden layer sensitivity analysis (sea state E3)

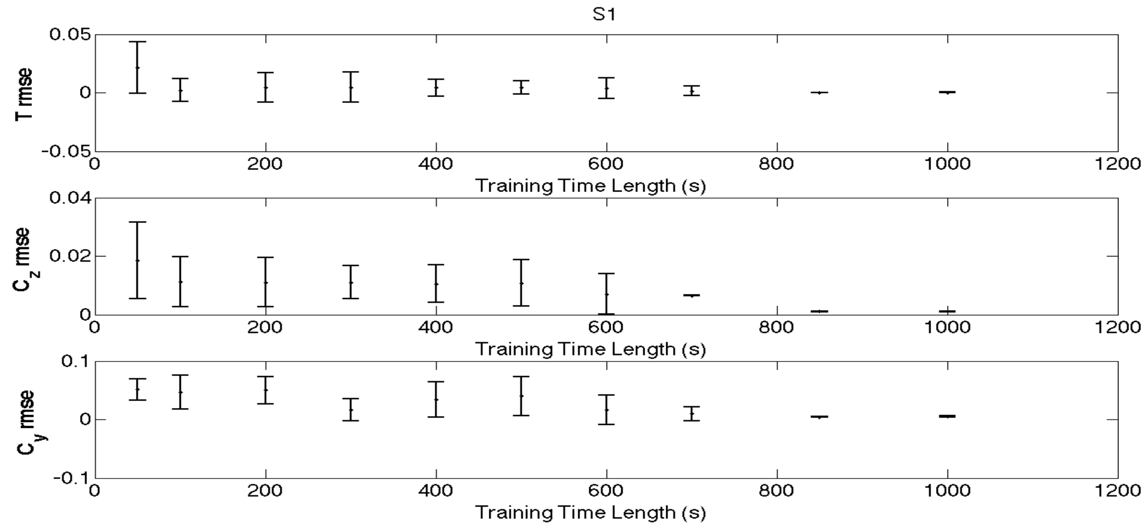

Figure 10-Training time length sensitivity analysis (sea state S1)

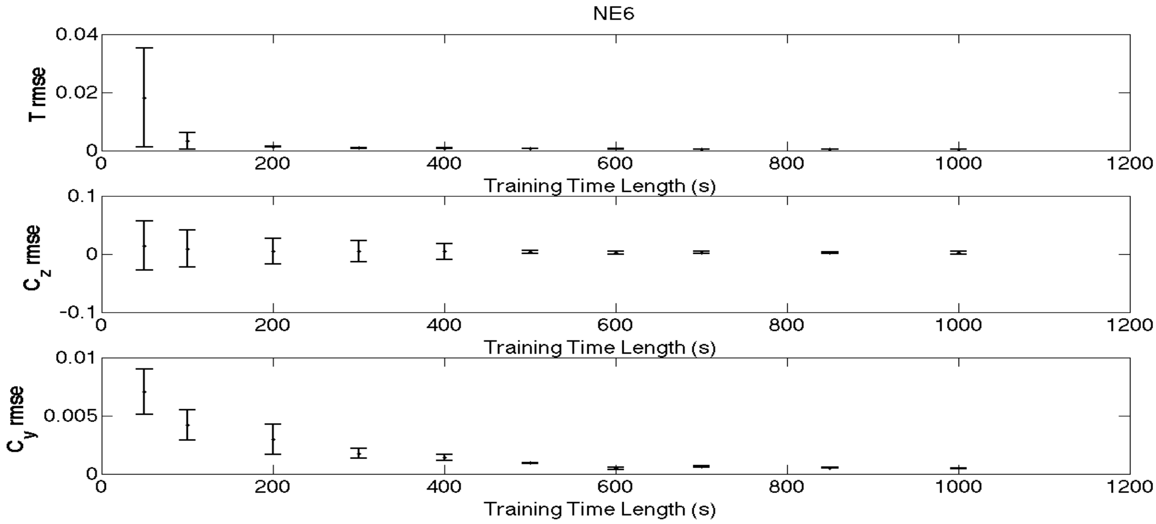

Figure 11-Training time length sensitivity analysis (sea state NE6)

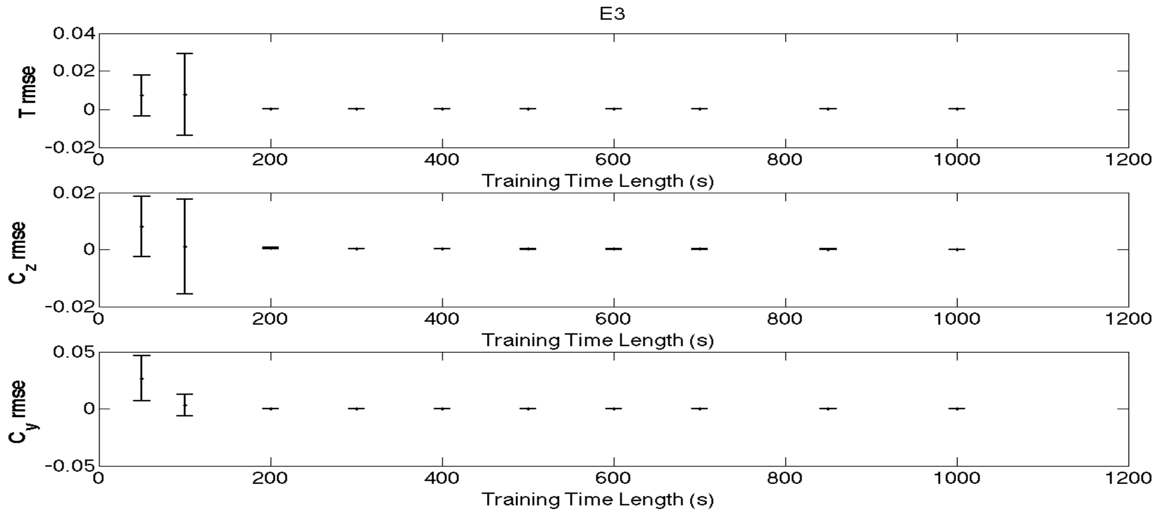

Figure 12-Training time length sensitivity analysis (sea state E3)

5.3 Global and Fatigue Analyses Results

In this item the main results obtained related to the global and local analyses using the proposed hybrid ANN-FEA approaches Method A and Method B and the full FEA methodology are presented. Figure 13, Figure 14 and Figure 15 show a short window of the results obtained with both methodologies for the axial tension $T(t)$, and bending $C_z(t)$ and $C_y(t)$ inside the bending stiffener, respectively, for one sea state coming from West direction. Similar results were obtained for all other sea states considered. Figure 16 presents the normalized fatigue damage assessment considering the results of Method A, Method B and the full FEA approach for all 11 sea states coming from East direction.

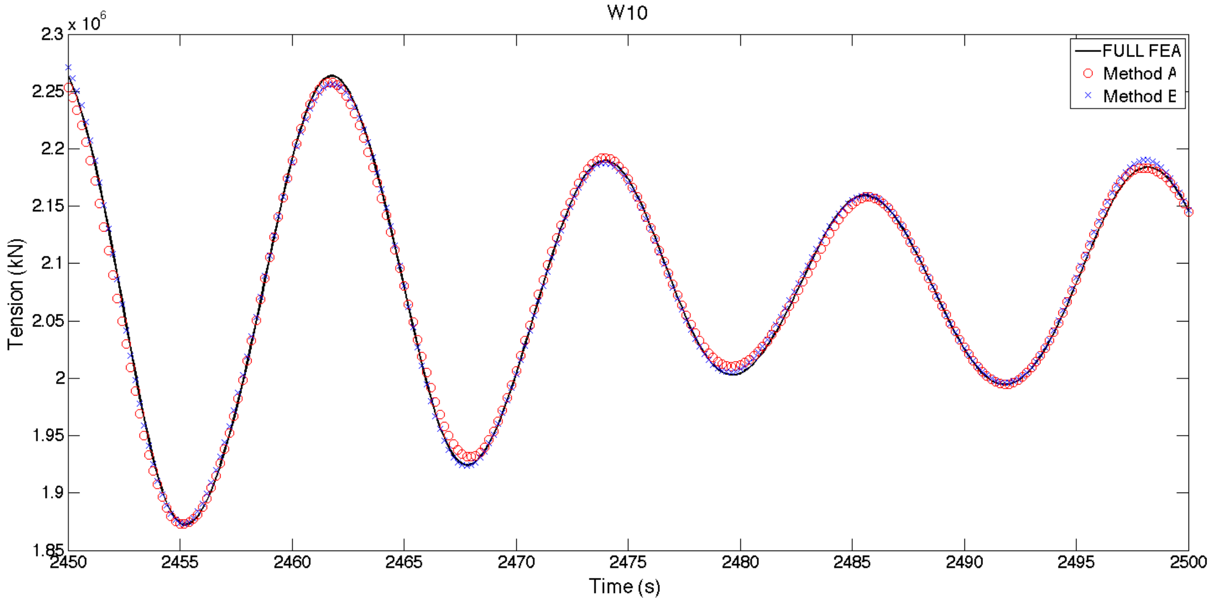

Figure 13 - Short window of axial tension $T(t)$ time series (sea state W10)

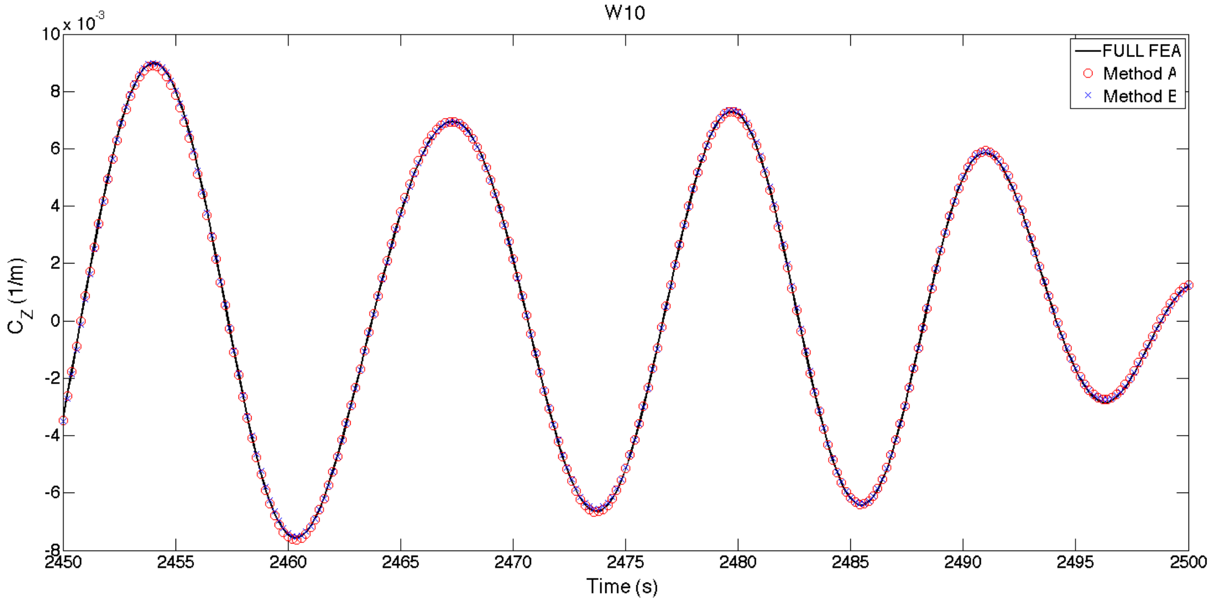

Figure 14 – Short window of $C_z(t)$ time series (sea state W10)

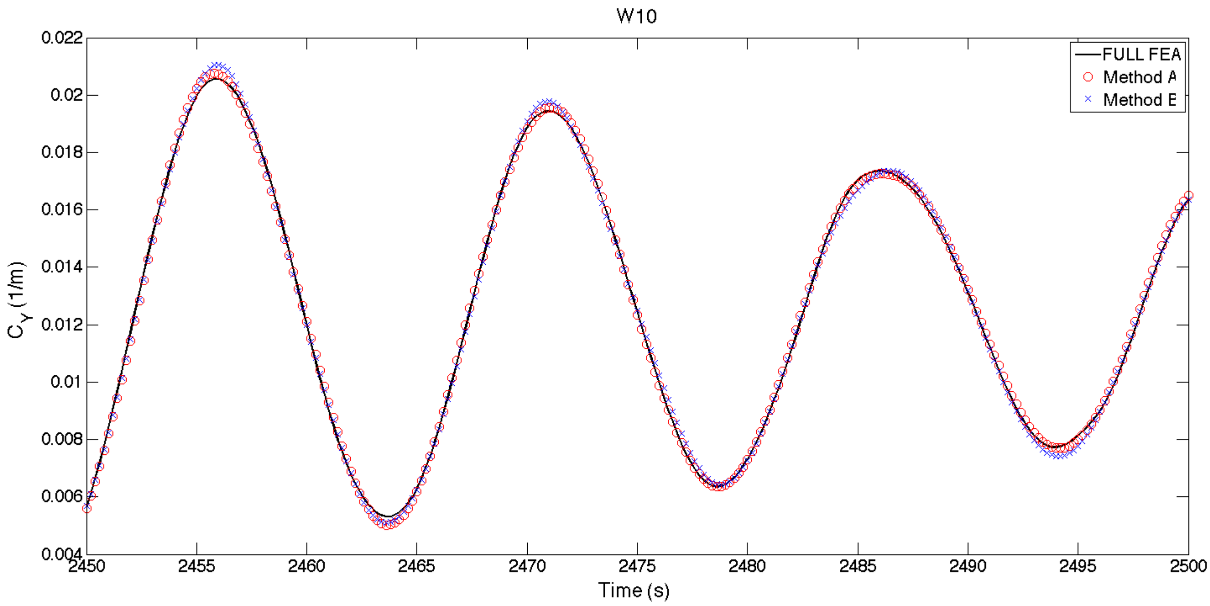

Figure 15 - Short window of $C_y(t)$ time series (sea state W10)

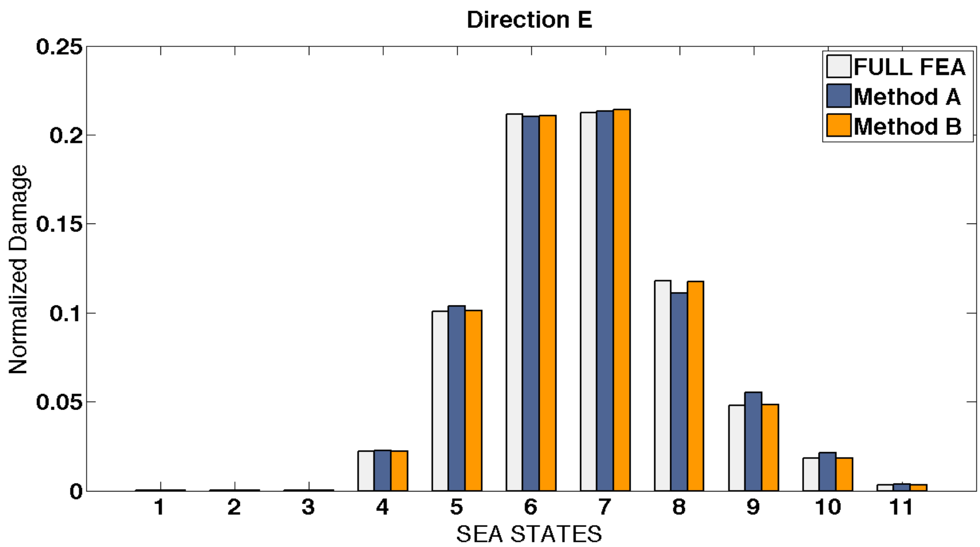

Figure 16- Damage results for the sea states coming from East direction

Table 2 compares the results obtained for annual fatigue damage. An accuracy estimation for hybrid approaches in relation to the full FEA results is estimated by:

$$\varepsilon_{method} = \left|(d_{full\ FEA} - d_{method})/d_{full\ FEA}\right| * 100\% \tag{10}$$

where $d_{full\ FEA}$ is the annual fatigue damage considering all sea states obtained from the full FEA results and d_{method} is the corresponding result obtained using one of hybrid approaches (Method A or Method B).

Table 2 also compares the computer costs in terms of analyses speed up. The speed is expressed comparing riser analysis simulations of 4000s and 10800s. For the latter case the speed up is extrapolated based on the former case.

Table 2 – Accuracy and speed-up of the hybrid approaches compared to full FEM data.

	Full-FEM	Method A	Method B
1-year fatigue damage (normalized)	1.0	0.9982	0.9997
ε (%)	0.0	0.178	0.023
Speed-up (4000s)	1.0	8	
Speed-up (10800s)	1.0	20	

As it can be observed in Table 2 the accuracy of both hybrid approaches are impressive. Although this aspect is not important, for the level of accuracy attained, it also observed that Method B is more accurate than Method A. A very important feature of the ANN-based approaches is that the fatigue analysis using the hybrid ANN-FEA can be 8 to 20 times faster than using full FEM analyses. Since the computer time is negligible for training an ANN, all time spent is connected to the initial FEM simulations to get the training and validation data sets.

6 CONCLUSIONS

As showed above the proposed hybrid ANN-FEA methodologies presents a very good accuracy and is also very efficient for predicting the global load effects $T(t)$, $C_z(t)$ and $C_y(t)$ in a global flexible pipe analysis. By using this approach, it is possible to perform flexible riser fatigue calculations more efficiently: significant computational time is saved.

Based on the sensitivity study results it was observed that the number of neurons in the hidden layer is a key variable for the ANN architecture and better results are obtained when this parameter is adjusted case by case.

Regarding the computational cost saved, for the conventional full FEA methodology, considering 88 sea states and a time domain simulation of 4.000s for each sea state, the total simulation time is 352000s. For the proposed hybrid ANN-FEA approaches, considering that the three NARX ANNs works in parallel, just a short simulation of 500s is required for each sea state. Thus for the proposed hybrid ANN-FEA approach the total simulation time required is 44000s. So, comparing both methodologies it can be seen that the hybrid ANN-FEA approach can be 8 times faster than the conventional full FEA methodology.

It is to be noted that the computational costs associated to local analysis, damage calculations and the training of NARX ANN are not taken into account for this comparison because they are very low compared to the computer costs of the global riser analyses. It must be highlighted that the main advantage of the proposed methodology is that the same training can be used to obtain larger simulated time-series, for instance 10800s (3-h), without practically any additional computer effort. In this case, the hybrid ANN-FEA approach would perform approximately 20 times faster than the conventional full FEA methodology. Statistically speaking, these long time-series allow the computation of better fatigue estimators.

For future works, based on the development presented in (CHRISTIANSEN *et al.*,2013), the idea is to mix inputs and responses short time-series of just a few sea states in the training of the NARX ANNs and use them to predict the responses for all sea states in the scatter diagram. This procedure can reduce even more the computer time required for the flexible risers fatigue analysis using stochastic global analyses.

REFERENCES

AMERICAN SOCIETY FOR TESTING AND MATERIALS (ASTM), 2011, Standard Practice ASTM-E1049-85 – Cycle Counting in Fatigue Analysis, USA.

CALEYRON, F., GUITON, M., LEROY, J.M.,et al., 2014, “A Multi-Purpose Finite Element Model for Flexible Risers Studies”, International Conference on Offshore Mechanics and Artic Engineering (OMAE), San Francisco, USA.

CHAKRABARTI, S.K., 1987, *Hydrodynamics of Offshore Structures*, Springer-Verlag, Berlin.

CHAVES, V., SAGRILO, L.V.S, DA SILVA, V.R.M, 2015, “Artificial Neural Networks Applied to Flexible Pipe Fatigue Calculations”, International Conference on Offshore Mechanics and Artic Engineering (OMAE), St. John's, Canada.

CHRISTIANSEN, N., VOIE, P., SØDAHL, N., et al., 2013, “Efficient Mooring Line Fatigue Analysis Using a Hybrid Method Time Domain Simulation Scheme”, International Conference on Offshore Mechanics and Artic Engineering (OMAE), Nantes, France.

FALTINSEN, O., 1993, *Sea Loads on Ships and Offshore Structures*, Cambridge Ocean Technology Series, United Kingdom.

FERET, J., BOURNAZEL, C.H., 1987, “Calculation of Stresses ands Slips in Structural Layers of Unbounded Flexible Pipes”, Journal of Offshore Mechanics and Artic Engineering, v. 109, pp. 263-269.

FERET, J., LEROY, J.M., ESTRIER, P., 1995, “Calculation of Stresses and Slips in Flexible Armours Layers with Layers Interaction”, Journal of Offshore Mechanics and Artic Engineering, v. V, pp. 469-474.

FILHO, F.S.L., LIMA, E., SAGRILO, L.V.S., et al., 2012, “Safety Factors for Fatigue Analysis of Flexible Pipes Based on Structural Reliability”, International Conference on Offshore Mechanics and Artic Engineering (OMAE), Rio de Janeiro, Brazil.

GUARIZE, R., 2004, *Neural Networks in the Dynamic Analysis of Structures*, M.Sc. thesis, Department of Civil Engineering, COPPE/UFRJ, Rio de Janeiro.

GUARIZE, R., MATOS, N., SAGRILO, L.V.S., et al., 2008, “Neural Networks in the Dynamic Response Analysis of Slender Marine Structures”, Applied Ocean Research, v. 29, pp.191–198.

HAYKIN, S., 2001, *Neural Networks - A Comprehensive Foundation*, Prentice-Hall, USA.

MATHWORKS, 2012, *Neural Network Toolbox^{TM} User's Guide,* USA.

MINER, M.A., 1945, *Cumulative Damage in Fatigue*, ASME Trans., 67, A159-164.

MOURELLE, M.M., 1993, *Análise Dinâmica de Sistemas Estruturais Constituídos por Linhas Marítimas*, D.Sc. thesis, Department of Civil Engineering, COPPE/UFRJ, Brazil.

MURRAY, S., 1993, *Neural Network for Statistical Modeling*, Van Nostrand Reinhold, USA.

NAESS, A., 1985, *Fatigue Handbook Offshore Steel Structures*, Tapir, Norway.

PINA, A.C., PINA, A.A., ALBRECHT, C.H., et al., 2013, "Neural Networks in the Dynamic Response Analysis of Slender Marine Structures", Applied Ocean Research, v. 41, pp.76–86.

PRINCIPIA, 2011, *Deeplines^{TM} 4.5 - Theory Manual*, La Ciotat, France.

SOUSA, J.R.M., 2005, *Análise Local de Linhas Flexíveis pelo Método dos Elementos Finitos*, D.Sc thesis., Department of Civil Engineering, COPPE/UFRJ, Brazil.

VIGNOLES, M.A., 2002, *Análises Determinística e Aleatória no Cálculo da Vida à Fadiga das Armaduras Metálicas de Risers Flexíveis*, M.Sc. thesis, Department of Ocean Engineering, COPPE/UFRJ, Brazil.