ARTIFICIAL NEURAL NETWORKS META-MODELS FOR PREDICTION OF VESSEL OFFSETS AND MOORING LINES TENSIONS OF FLOATING PRODUCTION SYSTEMS.

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Abstract. *Floating production systems (FPS) for oil exploitation are subject to the action of environmental loads such as wave, wind and current in different incidence directions and varying intensities. The mooring system is responsible for ensuring the integrity of the entire system and maintaining operations safe throughout its useful life. One way of evaluating the efficiency of a mooring system, by means of a numerical tool based on finite elements, is to apply extreme loads in different directions and check the resulting offsets of the floating platform as well as tensions in lines. However, this procedure requires the execution of static and dynamic analyses that have a high computational cost. Therefore, this paper presents an application of artificial neural networks (ANN) to estimate the offsets of the vessel and tensions in the mooring lines by taking as input the main parameters that define the configuration of a mooring system, namely the radii and angles, pretension and material type of the lines.*

The performance of ANN meta-models, applied to a FPS representative of those currently considered for ultra-deep water scenarios in Southeastern Brazil pre-salt fields, were evaluated using statistical tools (RMSE) in terms of accuracy and computational time.

Keywords: *ANN, Mooring System, Meta-models, Offshore systems.*

1 INTRODUCTION

Oil exploitation systems in offshore scenarios are extremely complex and expensive, which justifies their study and research. Floating production systems (FPS) that are the backbone of the operations in those fields can be based on moored ship or semi-submersible platforms, connected to risers that convey oil, gas and other fluids. Such systems must attend some safe operational limits based on parameters of their structural response (such as offsets, tensions or stresses); these parameters are defined in terms of time series, usually obtained from complex Finite-Element (FE) time-domain simulation tools.

In a traditional method for the numerical simulation of FPS, an uncoupled formulation is employed where the hydrodynamic behavior of the hull is not influenced by the nonlinear dynamic motions of the mooring line and risers. In this case, there are two analysis stages: the first is a motion analysis of the hull where the lines and risers are represented as scalar coefficients, submitted to environmental loads (wave and currents). In the second stage, for each riser, the hull motions are prescribed at the top of Finite Element (FE) models and the structural behavior of the risers is analyzed by means of a time-domain nonlinear dynamic simulation.

However, due to the development of the offshore industry and technologies, the scenarios have been changed and the challenge is different. Ultra-deep water oil fields are now being explored in the Southeastern Brazil pre-salt fields, and for these challenges an uncoupled formulation is not appropriated. Applications in deep and ultra-deep waters with a large number of risers must have a different approach of design in terms of simulation tools, in this case, tools based on coupled formulations (see (Ormberg et al., 1998.), (Senra et al., 2002.), (Correa et al., 2002.) and the references therein). On this formulation, the moored system and the risers are evaluated as a real integrated system, which englobes the interaction between the hydrodynamic structural behavior of all lines (FE meshes) and the hydrodynamic behavior of the hull.

Coupled analyses are more accurate and reveal with details the global behavior of the system. In this methodology all the nonlinearities involved in the dynamic response of the system are considered in a full time-domain (analysis) and the lines are rigorously represented by refined FE models. However, coupled simulation~~s~~ has a high computational cost; therefore Surrogate Models such as the Artificial Neural Networks - ANN have lower computational cost, while providing adequate results.

In this context, this work presents the development of an ANN to estimate the offsets of the platform and mooring line tensions using as parameters the configuration of the mooring system, namely the radii and angles, pretension and material type of the lines. Differently from previous works (de Pina et al.,2013, de Pina et al.,2014, de Pina et al.,2014) where the ANN works by estimating time series, here the ANN uses the Fitting Data method to provide the outputs. This way, the trained ANN can estimate with a good accuracy the offsets of the platform and mooring lines tensions, based only in the initial configuration of the lines, not depending on a time series evaluation.

2 BASIC FORMULATION OF ARTIFICIAL NEURAL NETWORKS (ANN)

2.1 Artificial Neural Network (ANN)

Applications for Artificial Neural Networks are spread in many fields of research to solve problems as pattern recognition, classification, clustering, time series forecasting, function approximation, optimization, signal processing, telecommunications, robotics (Widrow et al., 1994). For instance, ANNs has already been applied to the structural mechanics (Waszczyszyn et al., 2001), prediction of sea-state characteristics to ocean and offshore engineering problems (see for instance (Yasseri et al., 2010) and the references therein).

Meta-models based on ANNs deals with information between basic units of processing – the neurons. The network receives external signs – the inputs $x_i, i=1,N$. These signs are processed for each neuron that computes a linear combination of them using synaptic weights w_i to generate the *weighted input z*. Then, an output *y* is formed by an *activation function f*(*z*). This function has a vital importance in the process, for a range of values of *z* previously determined, it presents an increasing monotonic behavior and for values outside this range, it assumes a constant value.

Figure 1 illustrates an artificial model of a neuron – the McCulloch-Pitts neuron (McCulloch et al., 1943).

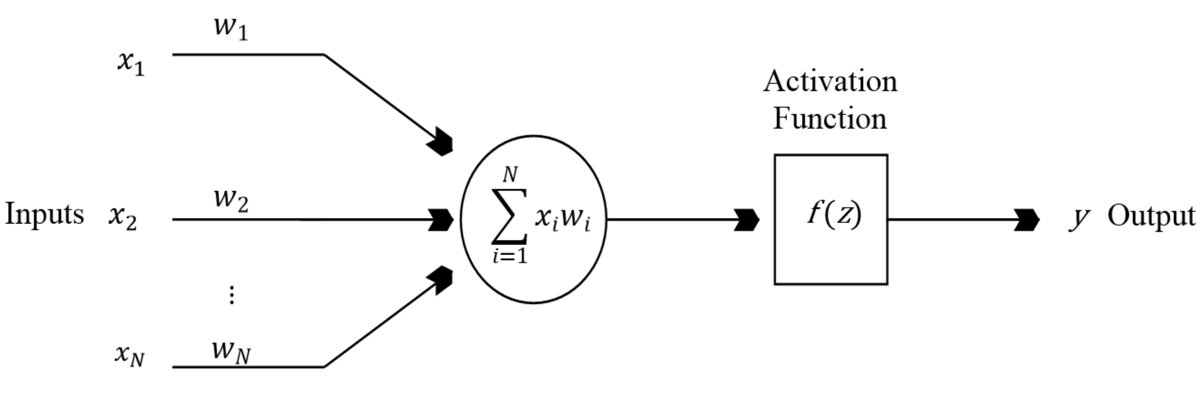

Figure 1. McCulloch-Pitts neuron

The Activation Functions that commercial software modeFRONTIER™ can apply are the *logistic function* and *sigmoid function*. In the following expression, the logistic function is defined.

$$y = f(z) = \frac{1}{1+e^{-z}} \tag{1}$$

The package available in the modeFRONTIER™ is based on a classical feed-forward neural networks with one hidden layer and an output layer (desired result *r(n)*). Besides that, an efficient Levenberg-Marquardt back propagation training algorithm is applied.

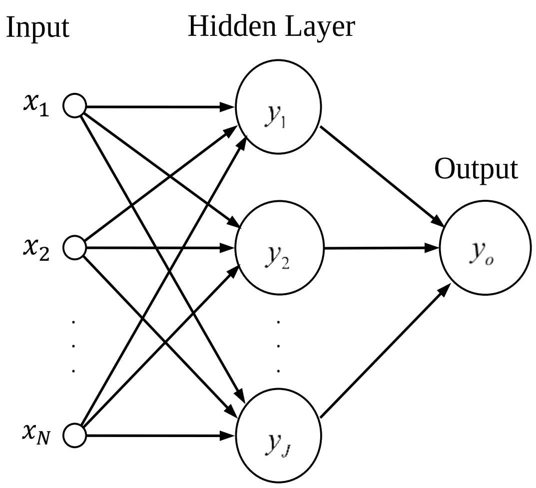

Figure 2. Architecture of the multilayer ANN

The most important process when performing an Artificial Neural Network is the training phase, for each epoch the training set (a set of known input-output pairs (x_i, y)) is presented to the ANN to adjust the weight values w_{ij} in the direction of the minimum distance of the desired output. After each iteration, these weights are updated until the error becomes minimum.

The software modeFRONTIER™ works with a Levenberg-Marquardt training algorithm using the method of *backpropagation* (Rumelhart et al., 1986). This method is composed by two phases: in the first one, one input is applied to the ANN, so this input is multiplied by the weights and the signal is propagated through the network until the last layer, where a response $r(n)$ is produced. In the second (backward) step, the network compares the produced response with the desired output, the error is calculated and "backpropagated" to the initial layer. In the back way, the weights are updated and this process only stops when a criterion is achieved.

3 ASSEMBLY OF META MODELS

3.1 Summary of the Procedure

The meta-model designed to this work depends of the results that a FE tool provides (offsets and tensions). A simple expression can express the formal model:

$$r(n) = f(W, X(n)) \tag{2}$$

Where $X(n)$ are the inputs; $f(.,.)$ represents the function ANN for each output; and W represents the corresponding parameters – the set of synaptic weights w_i. Table 1 summarizes the procedure of the meta-models. The ANN was implemented using the software modeFRONTIER™.

Table 1. Summary of the Procedure

1. Run coupled FE static analyses (e.g. 2000 individuals), to obtain a dataset with desired outputs $r(n)$ – platform offsets and maximum mooring line tensions;
2. Use these dataset to train/validate the network
3. Use the trained network to predict platform offsets and maximum tensions in the line, using new parameters in the configuration of the mooring lines

3.2 Inputs

Table 2. presents the parameters that influence directly the behavior of the platform motions and line tensions. These parameters are described in the modeFRONTIER™ model as individual variables which will be the inputs of the ANN.

Table 2. Coefficients in constitutive relations

Parameter	Description	Minimum	Maximum
01 – 04	Azimuth per corner	-3º	3º
05 – 08	Radius per corner	-500m	500m
09	Pretension	1000kN	3000kN
10	Material (Diameter)	0.122m	0.262m

The procedure for the training and validation stages of the network (Step 2 of Table 1.) can be done after the initial window of the parameters and the desired output series (collected at Step 1). Once the network is trained, to obtain the outputs (Step 3 of Table 1.) the network needs new parameters.

3.3 Outputs

The SITUA-PROSIM (2006) is a non-commercial software used for the analysis of offshore systems. In this work, coupled analyses are performed to provide the output dataset. The software incorporates numerical tools to define the input data: environmental loads, bathymetric seabottom data, configuration of the mooring lines, and the hull properties.

Static simulations are performed under the action of dead weight and current acting in eight directions of incidence (N, NE, E, SE, S, SW, W, NW), to provide the outputs (platform offsets and line tensions) that comprise the training dataset for the ANN. The training process provides the weights of the ANN, which can then be applied to analyze new configurations of the mooring system.

4 CASE STUDY: DEEP-DRAFT PLATFORM FOR ULTRA-DEEPWATER SCENARIOS

4.1 Characteristics of the FPS

The mooring system is divided on 4 corners, each one with 4 lines. An intermediate polyester segment (length of 2250 m and properties described in Table 2.) composes the lines with a top chain segment (length of 200m) and a bottom chain segment (length of 1600m). The system is comprised by 25 flexible and rigid risers, with different functions (production, export, injection, umbilicals).

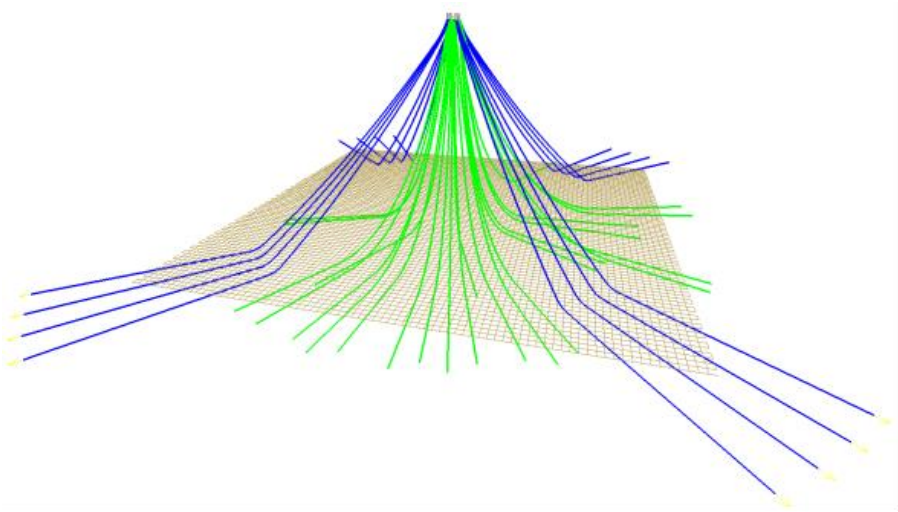

Figure 3: FPS for ultra-deepwater scenarios, 3D View

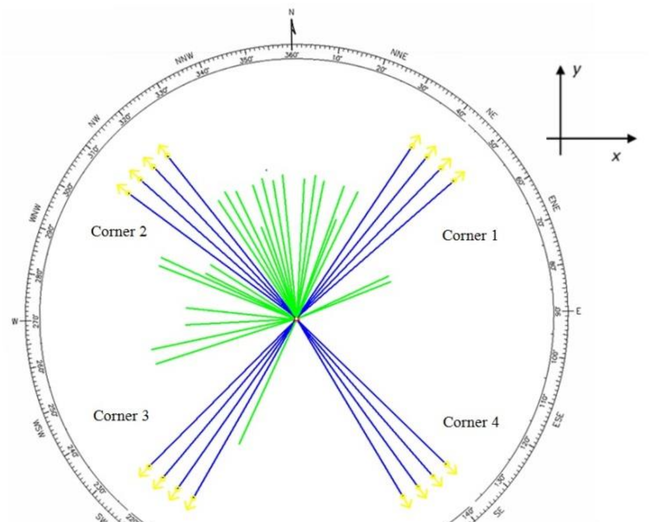

Figure 4: FPS for ultra-deepwater scenarios, Top View

Table 3. Characteristics of the Hull

Length (m)	97.0
Breadth (m)	97.0
Height (until main deck) (m)	75.0
Distance between center of columns (m)	75.0
Pontoons (Length x height x width) (m)	(52 x 11.5 x 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)	940000

Table 4. Properties of the initial Line Segments

Segment	External Diameter (m)	Weight in Air (kN/m)	Weight in Water (kN/m)	EA (kN)
Chain	0.114	2.5498	2.2183	919077
Polyester	0.210	0.2845	0.0748	187129

4.1.1 Environmental Loads

Considering the use of static analysis as mentioned above, the environmental loads consider current only, acting on coupled models including the risers, mooring lines and the platform hull, dynamic loads of wave and wind were not considered. Triangular profile is applied in eight directions (N, NE, E, SE, S, SW, W, NW), with intensity at sea surface according to Table .

Table 5. Current load

Direction	Velocity at sea surface (m/s)
N	1.30
NE	1.17
E	0.91
SE	1.26
S	1.39
SW	1.26
W	1.18
NW	1.17

4.2 Setup of the Experiments

The ANN was built with 10 neurons and 1 intermediate layer. The complete analysis of the FE tool generated 8000 individuals, however, only 30% of them were used for training/validation of the meta-model, the rest of dataset (70% - 5600 individuals) were used in the end to compare the outputs estimated by the ANN.

Table 6. Data division

Stage	Individuals
Training	2000
Validation	400
Test	5600

4.3 Results

Table 6 summarizes the statistical results of the trained ANN applied to the 5600 individuals of the test division. Figures 5, 6, 7, 8 and 9 contain the graphs in a visual comparison between the FE results and the values estimated by the ANN.

The percentage of the Minimum Break Loading in the line – MBL Eq. (3) represented by the output *TracMax* in the Fig. 10. The MBL measure is calculate using the Parameter 10 (Material Diameter). In a practical sense, the Eq. (4) provides the maximum tension (kN) of all the lines.

$$MBL = 295256x^2 - 3247{,}4x - 41{,}36 \quad (3)$$

$$TracMax\ (kn) = TracMax\ (\%) * MBL \quad (4)$$

Table 7. Errors of Training Phase

Output	Mean Absolute Error	Maximum Absolute Error
Offset - E	1.207E0*(m)*	1.997E1*(m)*
Offset - SE	1.788E0*(m)*	2.774E1*(m)*
Offset - S	1.474E0*(m)*	2.004E1*(m)*
Offset - SW	1.340E0*(m)*	1.800E1*(m)*
Offset - W	1.738E0*(m)*	2.082E1*(m)*
Offset - NW	2.229E0*(m)*	2.730E1*(m)*
Offset – N	1.468E0*(m)*	1.940E1*(m)*
Offset – NE	1.525E0*(m)*	1.435E1*(m)*
TracMax	*1.679E-3(%)*	*4.662E-2(%)*

Table 8. Statistical of the Results

Output	Number of individuals with error rate higher than 5%	Percentage of these individuals in compared to the test set
Offset - E	74	*1,3 %*
Offset - SE	56	*1,0 %*
Offset – S	24	*0,4 %*
Offset - SW	41	*0,7 %*
Offset – W	31	*0,5 %*
Offset - NW	73	*1,3 %*
Offset – N	84	*1,5 %*
Offset - NE	118	*2,1 %*
TracMax	3	*0,05 %*

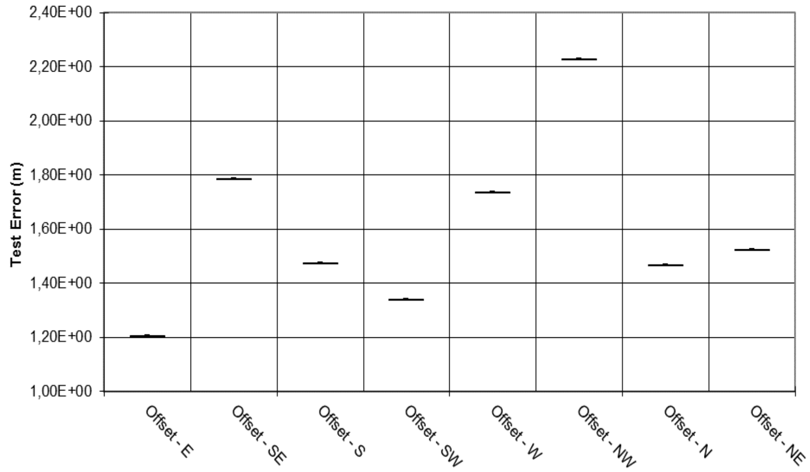

Figure 5. Mean Absolute Error for Offsets

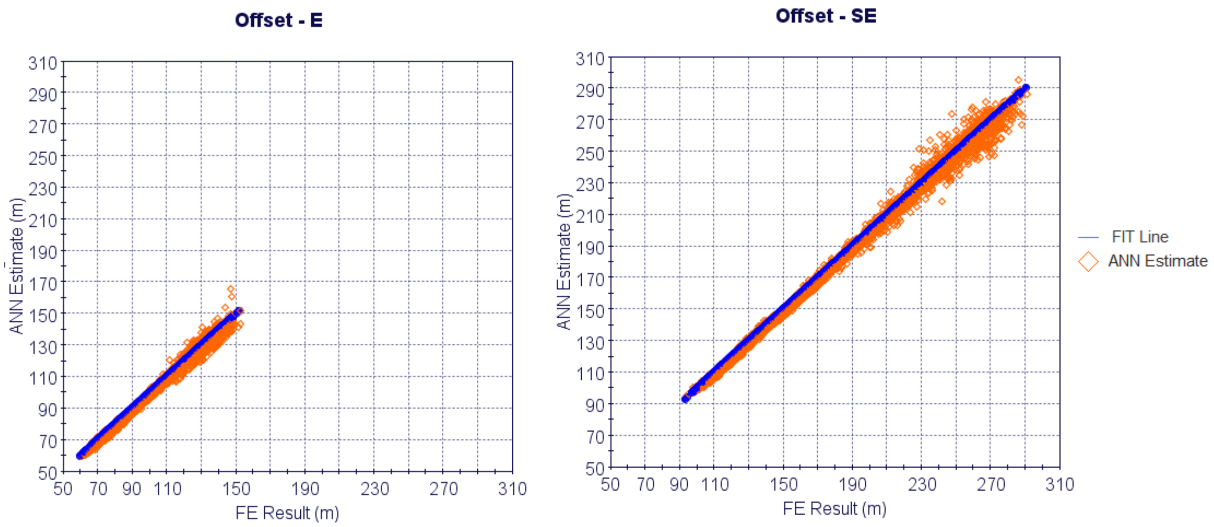

Figure 6. Offset E and SE

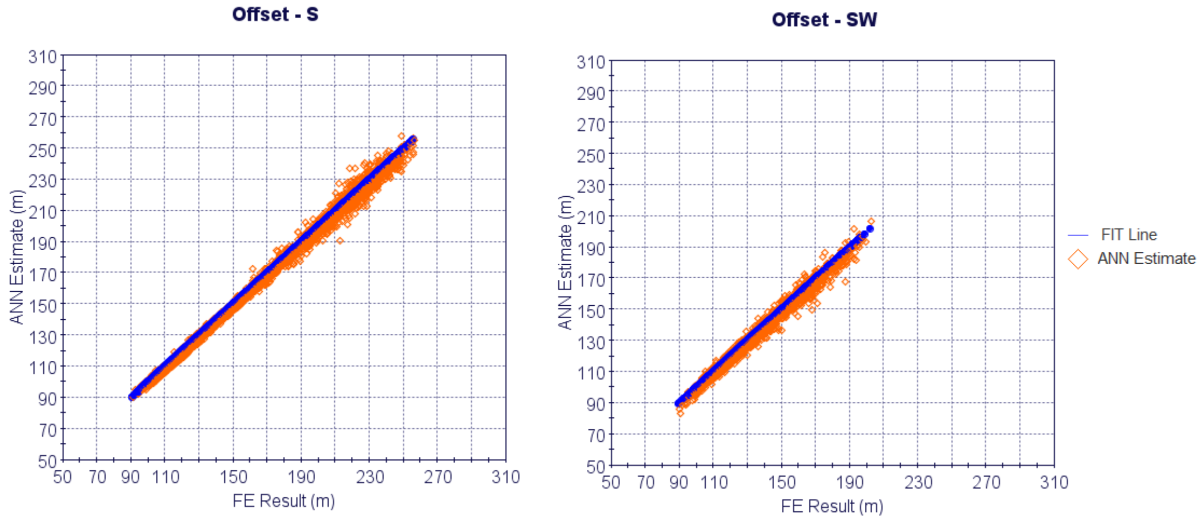

Figure 7. Offset S and SW

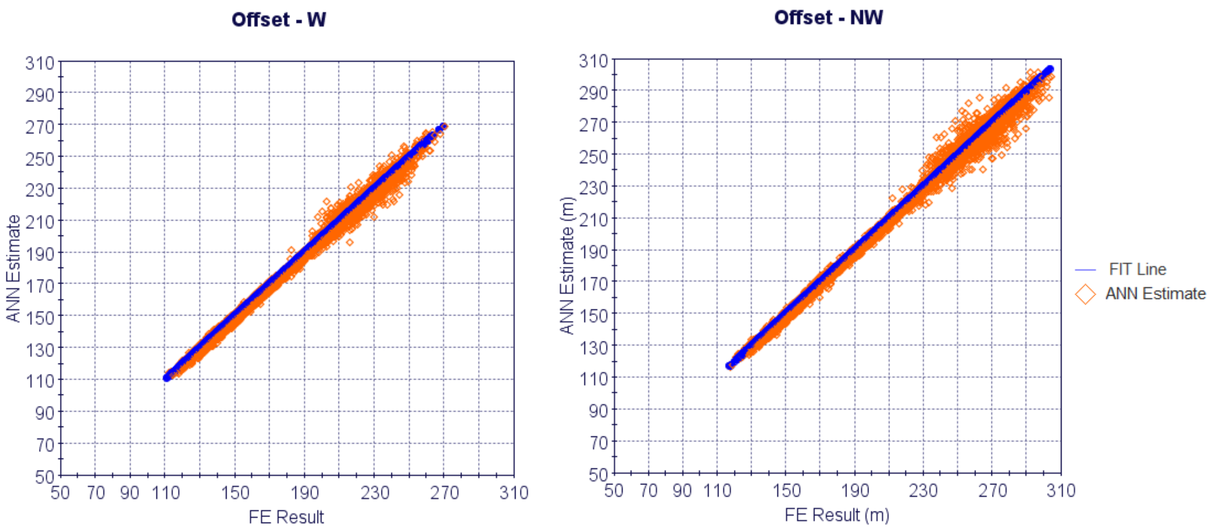

Figure 8. Offset W and NW

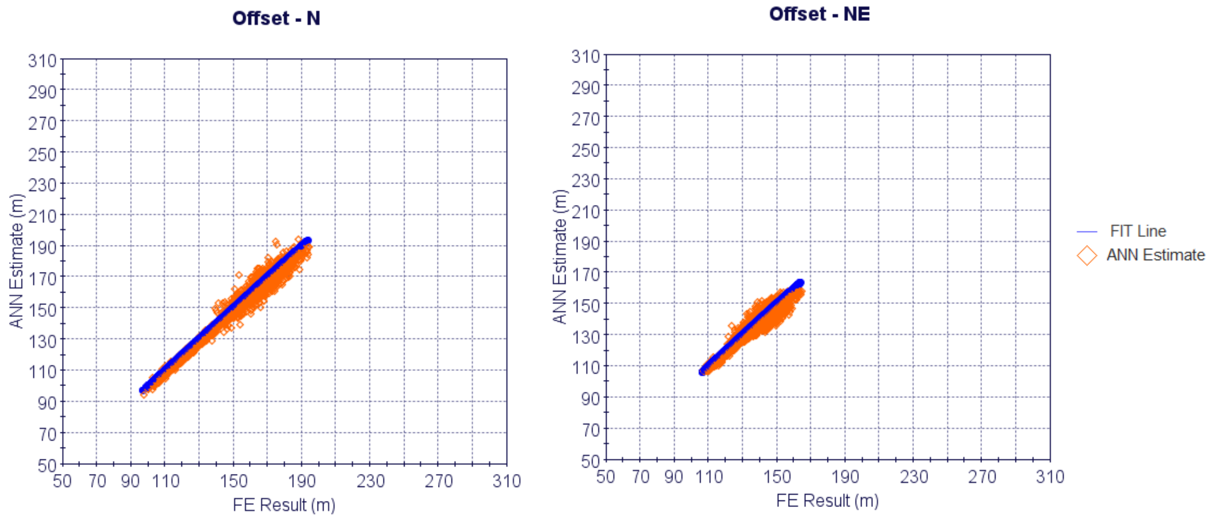

Figura 9. Offset N and NE

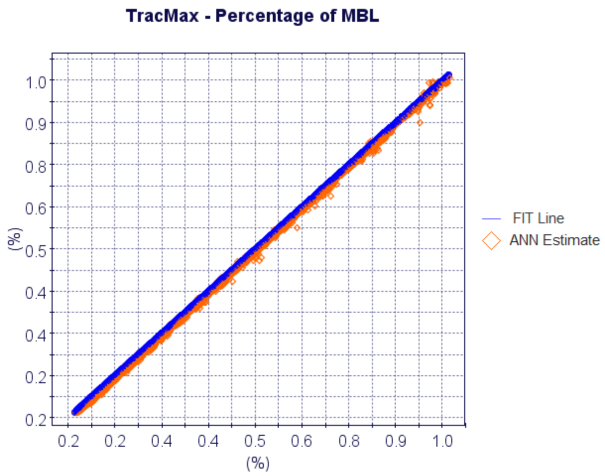

Figura 10. TracMax

A rough comparison of the computational cost can be made considering a sequential execution of all FE models, the approximate time consumed was 503000 s, while the total time consumed by ANN was 435 s.

4.4 Remarks

In the Figures 7, 8, 9, 10 a characteristic observed is that the most accurate results are between de initial regions of the graphs. In other words, the larger offset the greater is the error. One reason this happens is that the huge offsets are derived of extreme cases, exceptions that ANN could not be able to generalize so far.

Even thought, the results provided by meta-models presented a good accuracy with huge gains on computational time. The maximum absolute error found in Offset was *27.3 meters* (Offset – NW) and the maximum mean error found was *2.3 meters* (Offset – NW), which is acceptable in a primary evaluation of the structure and considering the depth of 1800m.

In Table 8, the estimated individuals using ANN in which error rate exceeds 5% were selected for comparison with the FE result, considering the test set consisting of 5600 individuals. Note that in this case the maximum percentage error found was *2.1 %* (Offset – NE).

Maximum tension of the mooring lines (TracMax) had a quite similar result, in the percentage of MBL small errors were found, which can be observed in the Fig. 11, where the comparison of the ANN Estimate and the FE Result are almost in the same line of regression.

5 CONCLUSION

This work presents and application of ANN for the analysis of offshore systems. The use of Neural Networks as an alternative to expensive FE analyses had already been considered in previous works, for the estimation of time series for a dynamic analysis of an individual mooring line configuration; now, we have employed a fitting data method to estimate results for any given configuration. The meta-model was able to approximate the results with only 30% percent of all the data available for the training phase of the ANN, thus reducing the computational costs.

In future works, to improve the estimation of the extreme values that are critic for the ANN, parametric studies can be perform to investigate how it affects the entire test stage. Besides that, alternative methods for selection of the dataset of training can be tested to improve the ability of generalization of the ANN.

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