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Model prediction of fatigue damage on offshore steel risers due to wave loading using FEA and ANN: A case of Forcados Offshore, Nigeria

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Abstract

This study aims at providing a model prediction technique for the fatigue life of offshore steel risers using a hybrid of finite element analysis and the artificial neural network (FEA-ANN) model. A 200 days' environmental load from Forcados sea state in West Africa offshore was used in training the FEA-ANN model to predict fatigue. The prediction result showed that the mean square error (MSE) was 0.3329 and the analysis from the regression was 0.9999. The result from the training showed a high performance and the regression analysis of the model was seen to be good.

Keywords: Offshore riser; Fatigue; Wave Load; Finite element analysis; Artificial neural network

1 Introduction

Offshore steel risers are structures of steel for strength against environmental loads and are used to transport oil and gas from wellheads to the production facilities. The steel risers can be used in many types of configurations (steel catenary risers, hybrid risers which are combinations of flexible and steel risers etc.). They are considered as critical elements of the subsea transportation from the resource site to the oil and gas industrial facilities in offshore environment. It is noted that catastrophic failures of steel riser components can be caused by fatigue crack growth. Fatigue-life prediction of offshore steel risers has become a major issue to ensure the integrity and reliability.

Fatigue is a phenomenon that is used to describe a condition of structural damage that occur as a result of cyclic loading, this damage occurs mainly at stress values that are lower than the yield stress limit and ultimate tensile stress, (Ozgue, 2016). Steel risers are commonly affected by cyclic loadings from ~~currents~~ and ~~waves~~ motions during their period of operation. These fluctuated loadings can initiate or extend cracks in the material (Agbakwuru et al., 2016). The result in fatigue crack growth of offshore steel risers can be a serios safety and critical concern as the structure is primarily used to carry oil and gas. More so, the steel risers do encounter harsh and extreme working conditions, therefore, failure during their service life needs to be considered. One of the most significant failure modes in offshore riser structures according to Elsevier Ocean Engineering Series (2001) is due to fatigue which occurs as a result of accumulated damage from mainly two factors:

i. First-order wave loading
ii. Vortex-induced vibrations (VIVs) due to current

It is noted that case (ii) the nonlinearity of system can be very large, particularly around the critical touch down point.

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Several experimental and numerical research work on fatigue failure of pipelines and risers can be found. Zhang et al. (2018) carried out an experiment on the crack growth of carbon steel under a wide range of loadings. Holtam et al. (2010), experimentally investigated the effect of sour environment on fatigue crack growth rate of carbon steel with grade API X65. Consideration of the low-cyclic loading as well as the large plastic strains applied to the girth welds of pipelines, the fracture assessment and fatigue crack growth rate were discussed due to the existence of crack at the welded girth (Zhang et al., 2018; Agbakwuru et al.,2016). Various studies on fatigue crack growth of an embedded crack were investigated using parameters, namely, stress ratio, crack shapes and sizes (Dake et al., 2012; Zhang et al., 2018). In a structure under cyclic loadings when multiple interacting cracks exist, the cracks propagate towards each other and merge into a single large crack which expedites its growth rate much faster (Kamaya, 2008). Therefore, multiple cracks interaction has caught attention of many researchers and extensive research has been done under various conditions (Konosu and Kasahara, 2012; Kotousov and Chang, 2015). Several experiments were conducted to investigate the fatigue crack growth behavior of interacting cracks. For instance, coalescing cracks on a plate fatigue life prediction of was done by Soboyejo et al. (1990). Furthermore, experiments were conducted on a plate specimen with two semi-circular cracks caused by fatigue (Kamaya, 2008). In general, offshore steel risers are generally under fluctuation loadings due to waves, currents and sea ground motions, these fluctuated loadings pose some threat to unflawed structural systems and it is possible that pre-existing embedded defects will increase due to the loading cycles.

Over the years there have been a shift towards data driven solutions with the help of machine learning methods in discovering patterns and performance prediction in different fields of science and engineering. Machine learning models such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Naive Bayes, decision tree, random forest, an ensemble model, and Neural Network (NN), have been vastly adopted for classification as an extension of machine learning.

Guarize et al., (2009) adopted hybrid ANN-FEA methodology in the prediction of dynamic top tension of a mooring-line and in the evaluation of DNV-LRFD. The predictions showed very-good agreement with the FEA results, and the computational time was reduced by a factor of about 20 times. Pina et al. (2013), also studied different substituted models to predict coupled mooring and riser top tension dynamics behavior with significant decrease on FEA computational costs. Artificial Neural Network (ANN) methods can be used to classify and estimate the damage of fatigue on process systems (De Lautour and Omenzetter, 2010). Pujol and Pinto (2011) proposed a fatigue life prediction approach using an ANN. Durodola et al. (2018), ~~in~~ their paper presented an ANN approach in order to study the effect of mean stress in fatigue life prediction in the frequency domain. More so, Zhu et al. (2019) proposed a probabilistic model to predict damage in an orthotropic steel deck using a Bayesian network. Fathalla et al. (2018) created ANN for the diagnosis of the fatigue life of a service road bridge. A generic algorithm was implemented by Franulović et al., (2009) to describe the elasto-plastic behavior in low cycle fatigue. Shabbir and Omenzetter (2016) combined a sequential niche technique with genetic algorithm with the aim to minimize the error between the model and structure model. Jimenez-Martinez and Alfaro-Ponce (2019) proposed a fatigue damage evaluation using ANN. Müller et al., (2017) performed fatigue response surface modeling evaluation using Latin Hypercube Sampling and ANN. Furthermore, Wong and Kim (2018) developed an ANN model which predicted the vortex induced vibration fatigue damage of a top tensioned riser. Lopes and Ebecken (1997) estimated the fatigue damage of fixed offshore structures using a feed forward back propagation neural network. Li et al. (2018) proposed an approach for wide banded fatigue prediction of catenary mooring lines based on an ANN. Recently, Raeihagh et al., (2020) combined an artificial neural network (ANN) and a fuzzy inference system (FIS) as a new model to assess the risk associated with pipelines. This model was used for oil and gas-pipeline risk estimation in a bid to model the most significant and influential factors in pipeline performance. They verified the accuracy of their-model, by using an inter-phase shore pipe of phase 9–10 refinery in the South Pars Gas field and their results gave evidence that the proposed model gives a higher level of accuracy, precision, and reliability in terms of pipeline risk assessment. Fernades et al., (2021) extracted profiles of pipeline cross sections from DSM and then obtained a geometric information of each profile and modeled it based on ANN and Random Forest (RF) of free span condition classification. This was done to develop a routine to semi-automatically identify the free span condition when a pipe segment is not supported by the seabed. Their results indicated that the ANN and RF proved satisfactory as the free span condition classification results was with global accuracy of 86.8% and 89.9%, respectively (Fernades et al., 2021).

One major interesting alternative to evaluate dynamic responses of marine structures with a significant reduction in computational time is the utilization of hybrid methods combining FEA with Artificial Neural Networks (ANNs) (Yooil 2015). The idea behind ANN is to try to mimic the human brain's ability to learn, recognize and predict patterns of different types. Steel risers are affected by cyclic loadings from currents and waves during their period of operation. These fluctuated loadings can initiate cracks in pipelines and result in fatigue crack growth (Agbakwuru et al., 2016). This fatigue crack growth produces several damages to offshore and geotechnical infrastructure. This paper presents how an ANN learns, recognizes and predicts the pattern of the mathematical model that relates the motions of an offshore steel riser due to dynamic load of waves. One of the most interesting alternatives to evaluate dynamic responses of marine steel risers with a significant reduction in the time of computation is the utilization of hybrid methods, combining Finite Element Analysis (FEA) with Artificial Neural Networks (ANNs). The idea of these methods is to bring in the remarkable capacity of learning and prediction of neural network to replace the burdensome numerical integration of a time domain dynamic analysis by finite elements method.

This work presents an application of a hybrid ANN-FEA method for the prediction of cyclic stresses due to waves on a steel riser connected to a fixed platform, in order to reduce computational costs of time domain stochastic simulations. It is noted that steel risers to a fixed platform is often clamped to the wellhead platform structures. Most times, these clamps are of carbon steel materials which do corrode and fall off. For the purpose of this work it is assumed that the clamps are unavailable. The great advantage of a hybrid ANN-FEA method is the joining of the best features from both ANN and FEA methods, keeping a fair compromise between model sophistication and required computational costs. To the authors' knowledge, the previous works did not employ a similar approach to predict the load effects for riser points near the TDZ nor to evaluate the total fatigue damage in this region. The aim of this work is to develop a hybrid model of FEA-ANN for the prediction of offshore steel pipeline riser fatigue due wave loading responses on the structure. It involved training and validation of ANN model using the time series response obtained from the FEA

2 Material and methods

The FEA simulation of the steel riser model was done to ascertain different fatigue damage resulting from different sea state. The sea state was represented by a time series response graph of 200 day's significant wave height and the environmental load was also shown in a time series graph. A scattered diagram was also used to represent the significant wave height and the environmental load. The environmental load was used to simulate the fine meshed model riser to ascertain the yield stress, strain deformation, percentage fatigue damage and fatigue life. This was done for a 200 day's environmental load collected from West Africa offshore (Forcados). This FEA results were then used to train the ANN model..

Table 1 Steel riser Properties

	Parameter	**Value**
1	External Diameter (m)	0.37
2	Wall thickness (mm)	28.58
3	Elasticity Module (KN/m2)	2.07E+8
4	Specific Weight (KN/m2)	77.00
5	Internal Fluid Weight (KN/m2)	2.0 (gas)
6	Soil vertical Stiffness (KN/m)	1000.00
7	Top Internal Pressure (MPa)	18.0
8	Temperature of fluid (^{o}C)	55
9	Water Depth (m)	22
10	Internal diameter (m)	0.33

This model riser adopted in this study consists of an outer diameter of 0.37m and a wall thickness of 28.58mm which was used to export fluid to the offshore platform from a water depth of 22m, the steel riser's physical and geometric composition is highlighted in Table 1.

The cases of the environmental loading that were picked to perform the fatigue analysis were determined by static offsets and wave loadings from Forcados in West African offshore. The same profile was employed for all loading cases that was taken into consideration in the fatigue analysis.

A 200 days' significant wave height was collected from the offshore location and used to carry out a usual FEA-based fatigue analysis. This was performed initially for comparison and was implemented to ascertain the life cycle of fatigue of the steel-riser, ensuring that the combining methodology of the FEA – ANN was adopted and deduced to the degree of critical structure.

Artificial-neural network (ANN) can biologically be described as the human neural network system which is capable of mimicking the human brain. Mathematically it has the ability to approximate, with a certain limit of errors, any mathematical function in theory, and can also represents any kind of mathematical function, even functions with some high degrees of nonlinearities. ANNs are used to find out the mathematical relationship that exist between the motions of an offshore floating unit and the respective steel riser load actions including the axial tension $T(t)$ and bending moments M_y(t) and M_z(t). In such application, the ANN must be trained with the data and results from a very short simulation obtained by the FEA and then the ANN is used to predict longer loading responses time series.

ANN architecture that is extensively used is composed up of three layers consisting of the-input layer, hidden-layer and output-layer. The first strata obtain the inputs-values of the network, the output-layer sends the responses of the-network. The concealed and productivity layers are interconnected with a mathematical element acknowledged as artificial neurons, (numerical functions). These mathematical fundamentals, carry's a load (synapse loading) that controls the function of the mappings between the three layers, there are also bias parameters, with-unitary values. This configuration is shown in Figure 1.

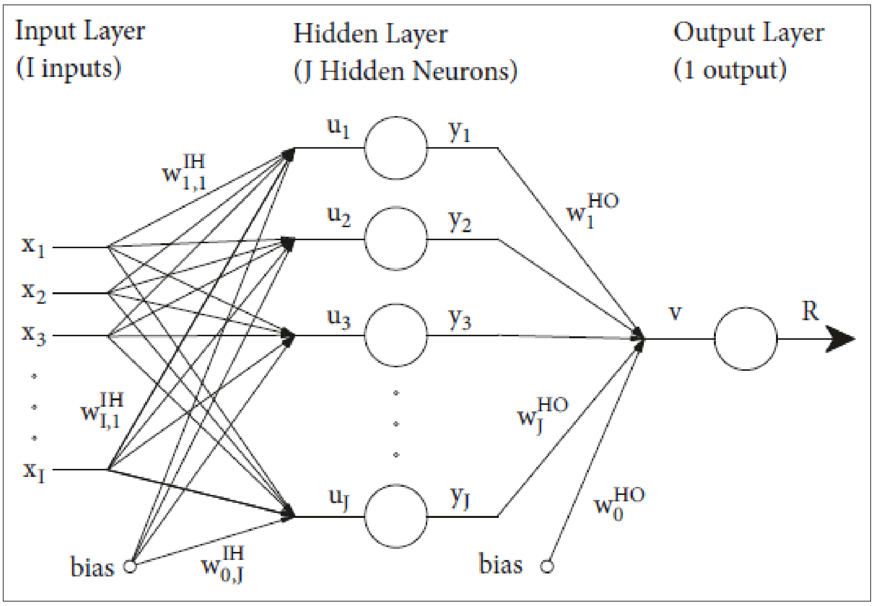

Figure 1 ANN Architecture

A neuron-j-in the hidden-layer receives an input from the input-layer u_j, given by

$$u_j = w^{IH}_{0,j}.1 + \sum_{i=1}^{I}\left(w^{IH}_{i,j}.x_i\right) \qquad \text{.....................2.1}$$

where I represent the number of network-inputs, $w^{IH}_{0,j}$ represent the bias-load of the input-layer, w^{IH}_{ij} is the load between the input i and the neuron j in the second-layer (j=1...J, J is the total number of hidden-layer units in the neurons), and x_i is the i-network input, and each neuron-revert an output-denoted by y_j

$$y_j = \varphi_H\left(u_j\right) = \varphi_H\left(w^{IH}_{0,j}.1 + \sum_{i=1}^{I}\left(w^{IH}_{i,j}.x_i\right)\right) \text{.............2.2}$$

where $\varphi H(.)$ signifies the activation-function, like the sigmoid functions, hyperbolic-tangent and logistic-functions. When considering an ANN with a single-output parameter (R) is estimated by

$$R = \varphi_O(v) = \varphi_O\left(w^{HO}_0.1 + \sum_{i=1}^{J}\left(w^{HO}_j.y_j\right)\right) \text{..................2.3}$$

where $\varphi_O(.)$ indicates activation-function of the neuron at the output-layer, usually a linear-function.

2.1 Training /Validation

When considering the inputs and output of an ANN, the time series as earlier describe as the inputs x_i and output (R), can be ascertain in relation between the inputs x_i and output (R) can be express as,

$$R(w,t) = f(w, x(t)) \qquad \text{................2.4}$$

Where $x(t)$ represents the vector-comprises of the time-series of the inserts data

w, is the matrix-containing the summation of artificial neural-network connecting the loads.

Given a set of time-series and the conforming-outputs, the network load also called weight (w) can be derived in a manner that the network-output is in line with the given-outputs sample. Optimization technique is adopted and applied to adjust the load (w) , and the method is known as neural-network exercise. The reduction of the optimization challenges can be expressed by applying the error in mean square (E). This is mathematically expressed as:

$$E\ (w) = \frac{1}{N}\sum_{t=1}^{N}\big(R(w,t) - v(t)\big)^2 \quad \text{...............2.5}$$

$$= \frac{1}{N}\sum_{t=1}^{N}(f(w, x(t)) - v(t))^2$$

N represents the length of the specimen time-series for exercise, where $v(t)$ is the sample desired output. A repeatedly optimization procedure, such as the vertical descend technique is employed to get optimal results for synapse-loading w (weights). The loadings are adjusted by reducing the random variables normally.

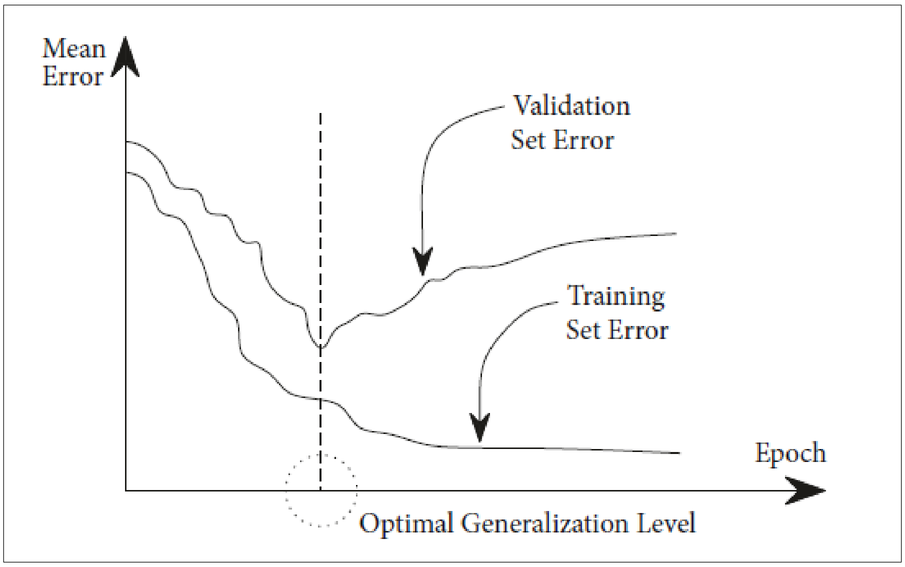

Figure 2 Usual behaviour of the training and validation errors

During optimization procedure (Figure 2), each repetition is term epoch. The output and input time-series are regulated to enhance the procedure of the exercise. Usually, errors of two kinds are spotted when exercising the network. the first one is as a result of stopping the training early, which resulted in few deviations from the ideal conditions of loads and creating large errors in prediction. The other type of error transpires due to excessive exercise of the ANN. Error in network is illustrated in the patterns possessed in Figure 2. The training progression should be stationary to ease the increase in validation error. This procedure prevents the overfitting (over trained) and guarantees an accurate network simplification for introduction of new-inputs.

2.2 Training the model

The results obtained from the FEA analysis was used to train the NARX model as detailed in the previous chapter, a total of 400 data was used to train the model where 70% (280) of the data was used as training data, while 15% (60) data was used as validation and each testing. The result from the training is shown in Table 2 and training architecture in Figure 3.

Table 2 MATLAB Results obtained from training the ANN model

Results

	Target Values	MSE	R
Training:	280	3.32868e-1	9.99944e-1
Validation:	60	9.74804e-1	9.99834e-1
Testing:	60	1.00571e-0	9.99852e-1

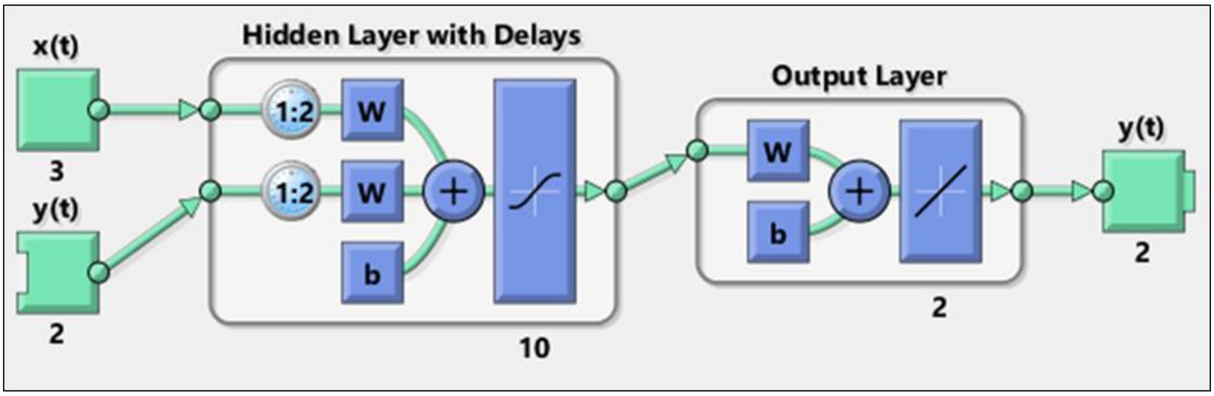

Figure 3 NARX-ANN Training Architecture from MATLAB

3 Results and discussion

Data from Forcados offshore was used to ascertain the impact of environmental load on the steel riser. A total of a 200 days daily Hs was used in the study. The extract is found in Table 4. Figures 4, 5 and 6 show the time series responses of the significant wave height and the scattered diagram of both the significant wave height and the environmental load. The highest wave height experience was 1.87m and the lowest was 0.45m and this was also seen that those days had the highest and lowest environmental loading respectively.

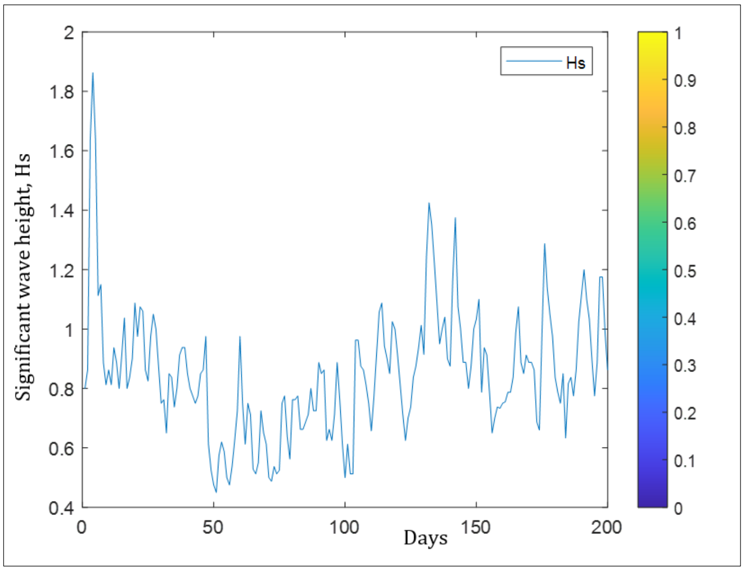

Figure 4 Time series response of 200 days' significant wave height

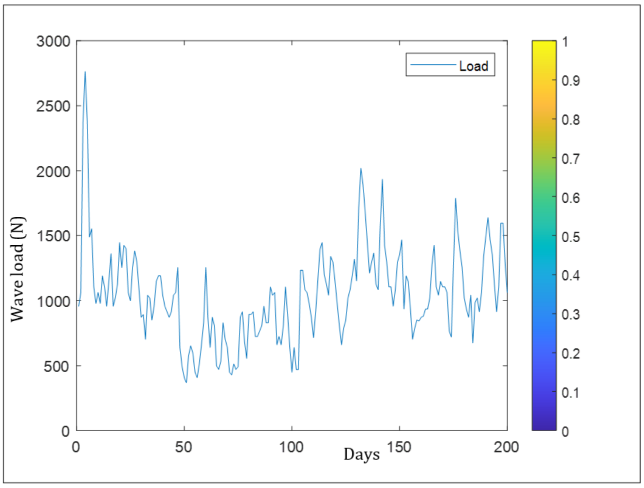

Figure 5 Time series response environmental load of 200 days

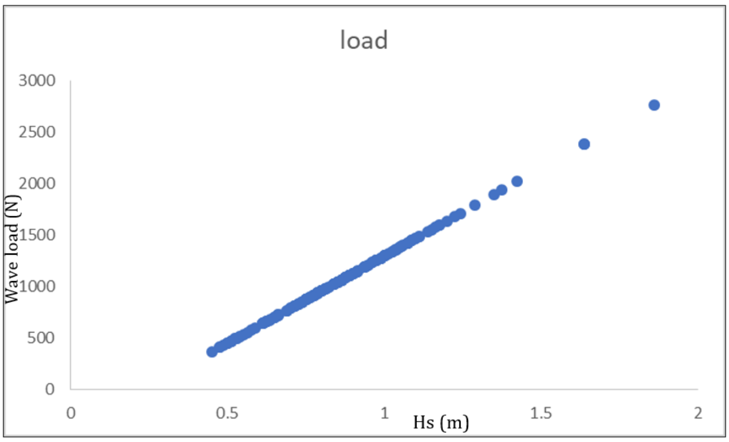

Figure 6 Scattered Diagram of 200 days Significant Wave Height and Environment Load

3.1 Result Obtained from the FEA

The finite element analysis was carried out on the steel riser model and the mesh result is shown in Figures 7 and 8. Figure 7 showed the solid mesh of the model steel riser while Figure 8 showed a zoomed mesh of the model steel riser. The properties of the model are shown in Table 3 and the mesh produced was high so as to ensure that the load on the element of the steel riser is well analyzed, the maximum and minimum mesh was 139.55mm and 46.52mm respectively. Table 4 indicates an extract of some results from the FEA computations.

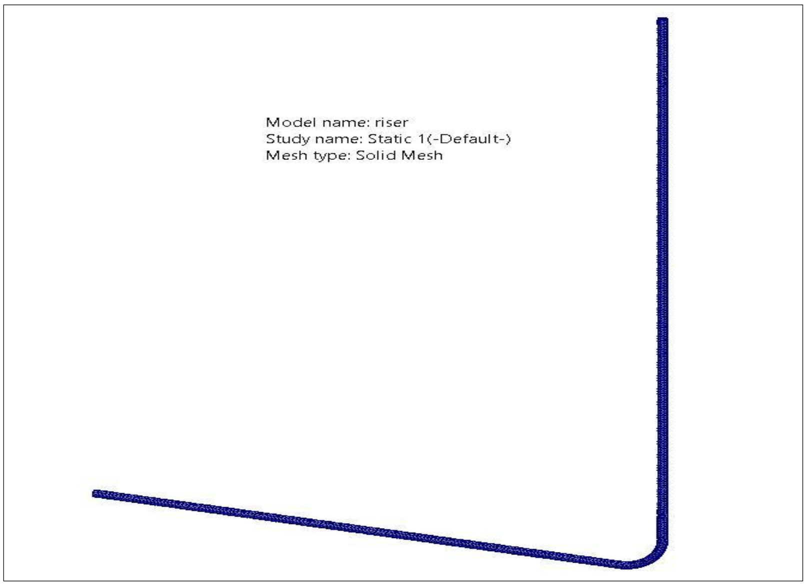

Figure 7 Solid Mesh of Model Steel Riser

Figure 8 Zoomed solid mesh of model steel riser

Table 3 Properties of FEA of steel riser model

S/N	Steel riser model properties	Values
1	Mesh Type	Solid Mesh
2	Jacobian points for High quality mesh	Blended curvature-based mesh
3	Max element size	139.553mm
4	Min element size	46.5172mm
5	Mesh Quality	High
6	Total nodes	44504
7	Total Elements	22189
8	Maximum Aspect Ratio	11.056
9	Percentage of element with Aspect Ration <3	21.2
10	Percentage of element with Aspect Ration >10	0.0361
11	% of distorted element (Jacobian)	0
12	Number of distorted elements	0
13	Time to complete Mesh	0:00:12

Table 4 Result extracted from the FEA simulation of the model steel riser

Sig. Wave height (m)	Environment Load (N/m)	Max Stress on Riser (N/m^2)	Max Strain on Riser (m)	% Fatigue Damage	Min Total Cycle Life (x e4)
0.32	150	4.01E+06	1.74E-04	0.010	111.951
0.41	300	3.90E+06	1.82E-04	0.020	111.322
0.50	450	3.79E+06	1.91E-04	0.030	110.693
0.59	600	3.68E+06	2.00E-04	0.040	110.064
0.68	750	3.57E+06	2.09E-04	0.050	109.435
0.77	900	3.46E+06	2.19E-04	0.060	108.806
0.85	1050	3.35E+06	2.29E-04	0.070	108.177
0.94	1200	3.24E+06	2.39E-04	0.080	107.548
1.03	1350	3.13E+06	2.51E-04	0.090	106.919
1.12	1500	3.02E+06	2.62E-04	0.100	106.29
1.21	1650	2.91E+06	2.74E-04	0.110	105.661
1.30	1800	2.80E+06	2.87E-04	0.120	105.032
1.38	1950	2.69E+06	3.00E-04	0.130	104.403
1.47	2100	2.58E+06	3.14E-04	0.140	103.774
1.56	2250	2.47E+06	3.29E-04	0.150	103.145
1.65	2400	2.36E+06	3.44E-04	0.160	102.516
1.74	2550	2.25E+06	3.60E-04	0.170	101.887
1.83	2700	2.14E+06	3.77E-04	0.180	101.258

1.91	2850	2.03E+06	3.94E-04	0.190	100.629
2.00	3000	1.92E+06	4.12E-04	0.200	100

The cyclic stress used for the fatigue computation is depicted in Figure 9. The training, error measures and validation are represented by Figure 10 and Figure 11. The response of the output elements in time series and regression tests are shown Figures 12 and 13 respectively.

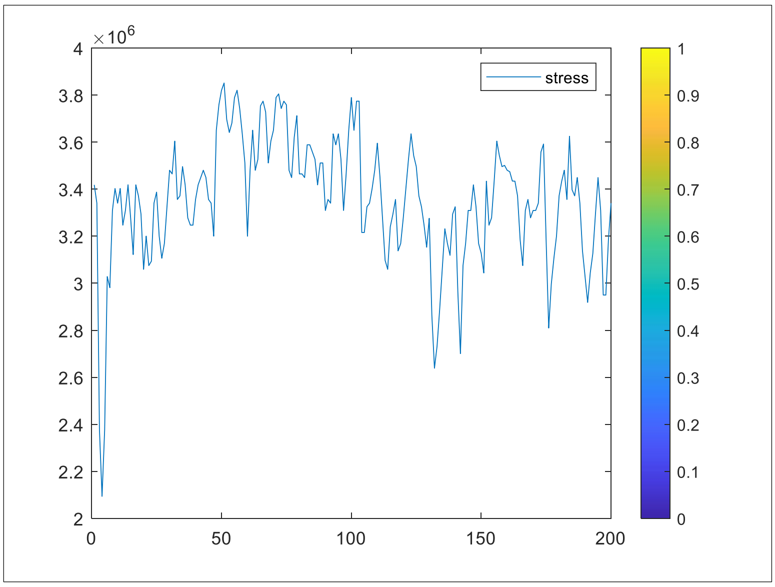

Figure 9 Time response analysis of the stress on the model steel riser

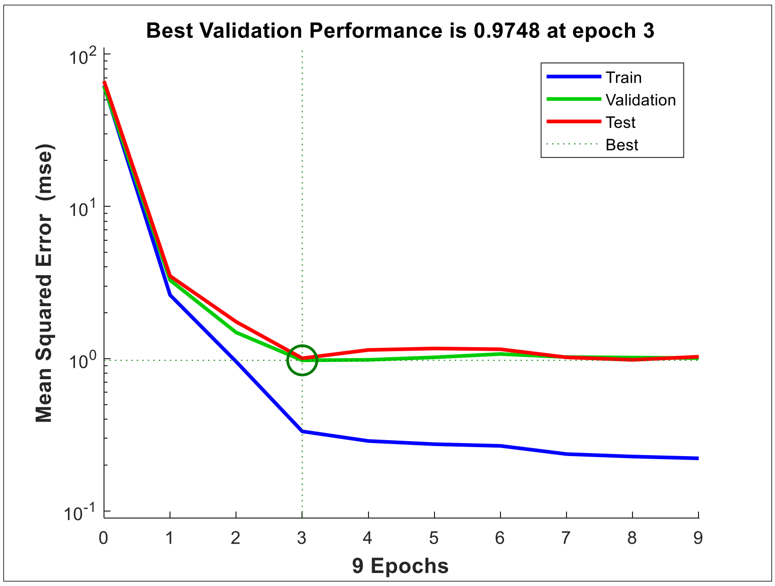

Figure 10 Performance of NARX-ANN Model of steel riser fatigue or prediction

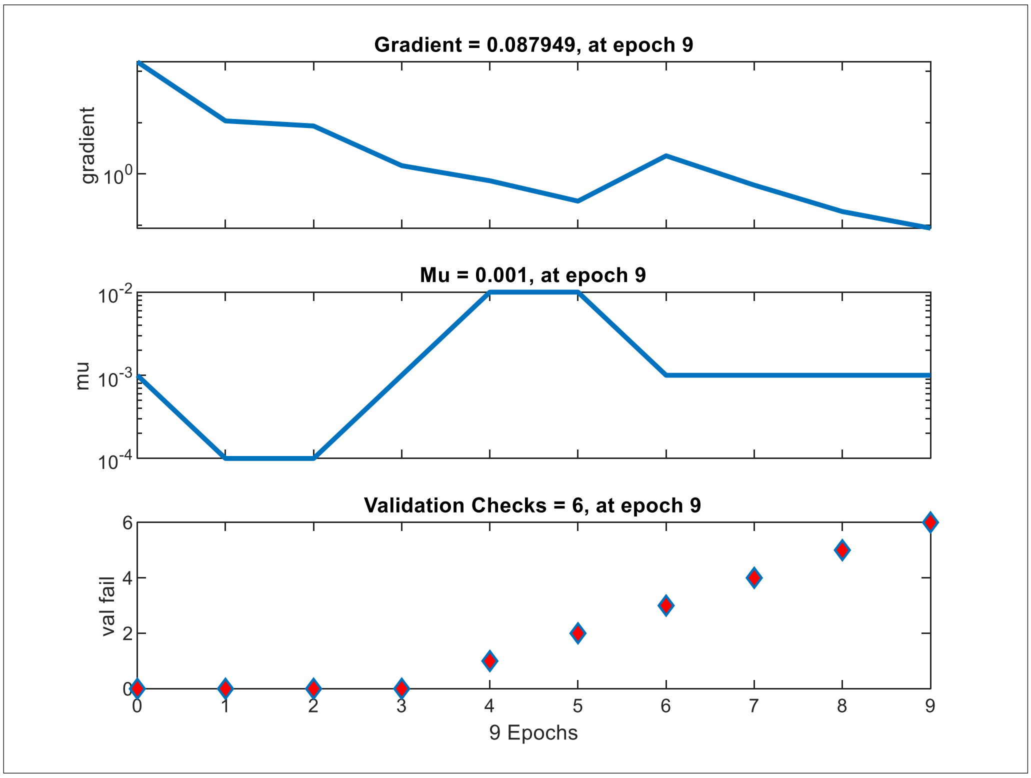

Figure 11 Training State of the NARX-ANN Model of steel riser fatigue prediction

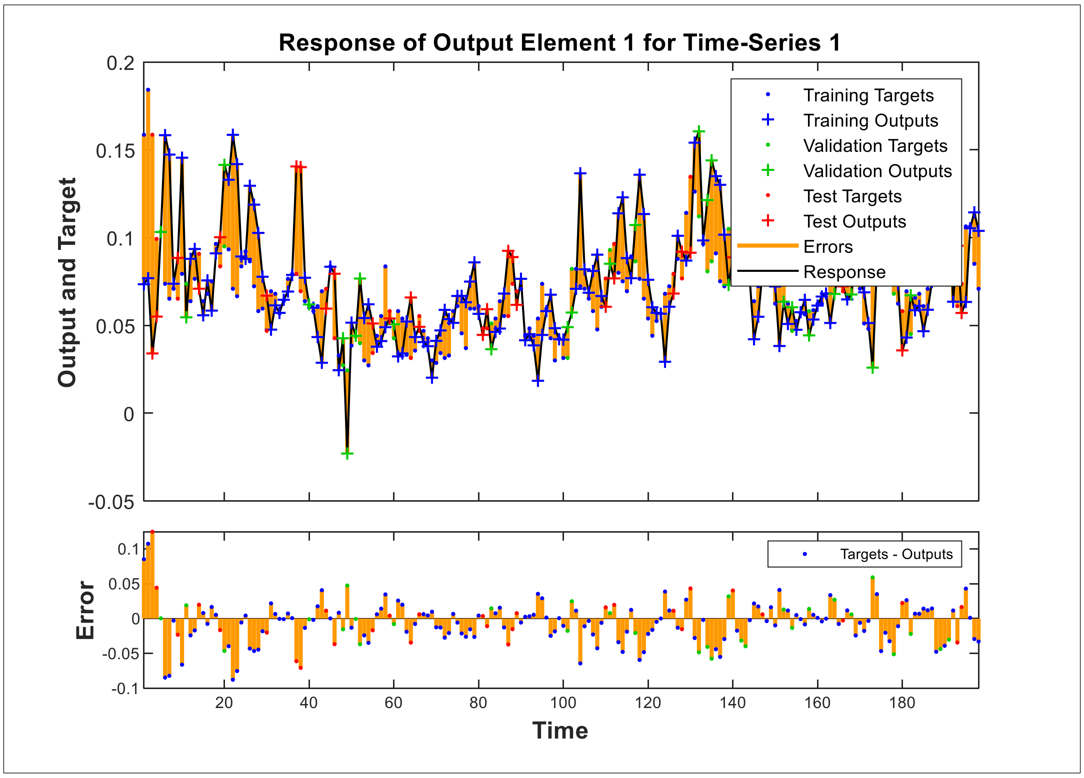

Figure 12 Time series response of the Hybrid FEA-ANN Model of steel riser fatigue prediction

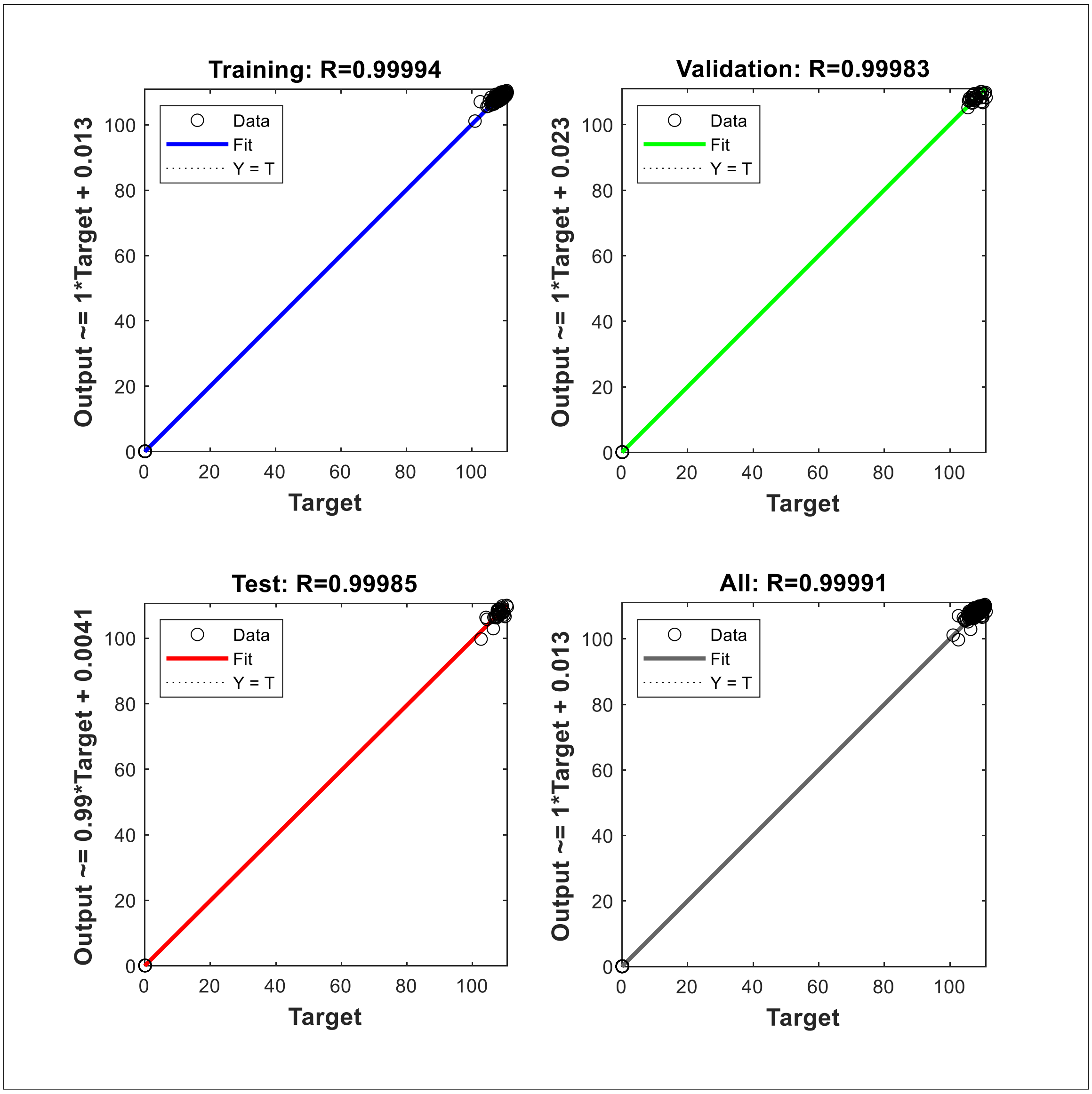

Figure 13 Regression Analysis of the NARX-ANN Model of steel riser fatigue prediction

The neural network when trained effectively with the right and available data, learns from the network and creates a neuron that will help in prediction. However, the neural network depends on availability of historical data which will help in data predication as discussed by several authors. Therefore, hybridizing the FEA and neural network will produce more accurate results with less time required and less complex computation.

From the model steel riser elements, the stress time series obtained by the FEA method and the corresponding one provided by the full FEA for the most critical point on the element with the lowest fatigue life at the top. The stress time series is taken from the loading case that contributes most to the total fatigue damage. Figure 13 shows the hybrid time series response of the predicted result.

In the modeled riser, each load case and global response applied to ANN was trained by a 200 data response time-series made available by FEA. The time of computation associated with the fatigue-damage evaluation and ANNs training was-very low when likened to the full global FEA. Hybrid ANN-FEA technique can be roughly 20-22 times faster than the usual FEA procedure. The results obtained in this project is productive and calls for further study in the development of an automatic-procedure to set-up the ANN architecture, training, and evaluation, to enhance the practical utilization of the methodology.

4 Conclusion

Fatigue life assessment is essential for the integrity of offshore pipelines and the use of traditional FEA has brought about several computational challenges. However, the use of machine learning like ANN used in this study has been able to add good value. The hybrid methods whereby ANN is combined with FEA has shown to have excellent accuracy and performance for fatigue assessment.

Compliance with ethical standards

Acknowledgments

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Disclosure of conflict of interest

The paper is purely academic research contribution with no conflict of interest either with the authors nor their employers.

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