Data Driven Virtual Sensors for Riser Prognostic Integrity Management

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Abstract
In-field riser strain or motion monitoring provides direct indication of riser fatigue and strength performance for prognostic integrity management. However, direct riser monitoring in the field has been limited in offshore developments to date with respect to its use as a standard on every floating platform and on every riser system attached to the vessel. This is due to the high perceived capital or operational costs of direct subsea monitoring when deployed on every riser to reliably monitor over the entire service life. Furthermore, monitoring devices are typically installed at practical locations, which may not be at fatigue critical areas. A lack of known response in service can result in qualitative inspection planning, conservative fatigue predictions and reduced asset utilization.

Data-driven virtual sensors provide an innovative solution for life of field riser monitoring and predictive inspection planning. The virtual sensor is a machine learning model that calculates stresses in the time domain at the fatigue hot spots and at high stress locations along the riser. The sensor is driven by platform motions and environmental loads that are typically measured in the field. It allows calculation of fatigue in near real-time using time synchronous data. The virtual sensor system can be integrated with a topside or centralized data platform.

The vision for the virtual sensor is to train a machine learning model initially with finite element global riser analysis data and subsequently with full scale field data from the riser in service. Data aggregation from a term and deployment limited riser monitoring system is employed to capture system-specific response. This hybrid strategy results in low cost virtual sensors for life of field riser monitoring.

This paper describes the motivation, methodology, validation and applications for riser virtual sensors. A framework for the development of a riser system machine learning model is described. Global response data is obtained from a vertical top tensioned riser operating in a water depth of 5,000 ft. Fatigue predictions are compared against the fatigue damage calculated from finite element analysis data.

Keywords: Riser systems; vertical riser; drilling riser; monitoring; fatigue; machine learning; deep learning; virtual sensor

Introduction
A typical deep water development will use a mobile offshore drilling unit (MODU) with a dedicated subsea BOP drilling riser for development drilling of subsea wells. A floating production platform such as a semi-submersible, FPSO, TLP or Spar is used as a production host and will utilize one of the various types of deep water production and export risers available such as steel catenary risers (SCRs) or top tensioned risers. These risers have high service reliability and this is attributed to the attention paid to quality of fabrication and the high level of conservatism used in design, which results in their resilience in the face of overload. However, conservative design practices come with a price and can result in costly upgrades to meet target design lives.

Furthermore, the above design approach has also led to very few risers within the deep water population being directly instrumented either with strain sensors at critical locations or with motion sensors to capture global and local response. Unlike on the vessel, placing monitoring devices subsea on the riser requires sensors that are encapsulated into hardware that are able to withstand the conditions in deep water and subsequently provide reliable data over the service life of the riser.
Very few of the instrumented risers have used fully hardwired systems, [1], due to the costs involved. The majority of directly monitored risers have used an array of standalone motion loggers over the riser length. Typically, only one or maybe two risers on a floating platform are monitored based on criticality and design margin.

Whilst current riser industry design practice is robust and thorough, structural integrity issues do occur typically in instances when field conditions have departed drastically from the original design basis, e.g., production fluid is more corrosive than designed for, wave or current environment is much harsher than predicted, or issues with VIV fatigue suppression devices due to excessive marine growth. Monitoring data is valuable in determining fitness-for-service as an overly conservative analysis may lead to a costly repair/replacement, or lack of field data may lead to key events being overlooked.

Another disadvantage of replacing uncertainty with conservatism is that it becomes very challenging to provide an engineering basis for continued use of riser systems that have reached the end of their initial design lives. For continued operation through these existing facilities, there is a need to safely extend the service life of these systems, with or without suitable design modifications. Such assessments often cannot afford to lose valuable fatigue budget from blanket conservative assumptions and require a better understanding of the bounds of the input parameters.

A more cost effective monitoring system that can span the full service life of each riser on a floating platform and track response at all critical locations in near real time is needed. This system would provide the most realistic loading history required for fitness-for-service and life extension assessments, improving the current design approach of condensing down historical metocean conditions into a seastate scatter diagram. This monitoring program should facilitate more data from risers deployed in the field, which will expand the industry’s database and solidify the updates needed in design codes to reduce design conservatisms.

Riser Prognostic Health Management

One of the main objectives of a monitoring program implemented on a riser system is to provide a means for estimating the fatigue damage accumulation at critical locations along the riser. The translation of measured data to damage at fatigue critical locations is not trivial, for it requires suitable transfer functions that convert the measured strains/accelerations/angular rates to fatigue damage, [2].

Typically, a finite element analysis (FEA) of a riser system is carried out to build this transfer function. The limitation of this approach is that it is based on design assumptions and aggregated metocean statistics, which might be overly conservative. An alternative is to use a statistical approach based on field measured data from vessel, environmental and riser monitoring. The limitation of the statistical approach is that it might not be representative of all possible environmental conditions that the site sees and is limited to just the structure and locations that are being monitored and cannot be extended to the entire field (for a production riser) or multiple deployments (for drilling/completion risers). Furthermore, as noted previously, not all subsea infrastructures are instrumented and vessel motion and environmental data are sometimes not available.

A hybrid FEA-statistical approach is preferable and the feasibility of the approach to the effects of wave and current loads has been examined for slender marine structures ([7]), flexible risers ([11], [12]), buoy support risers ([10]), shallow water drilling risers and wellhead/conductors ([13]), and mooring lines ([6], [7], [9]). The approaches detailed in [6]-[12] use a time series regression approach while [13] is based on regression of the time series statistics. The primary advantage of the time series regression approach is that it can alleviate requirement for long and expensive FEA simulations. On the other hand, regression of statistics enables deployment across a range of water depths, tensions and operating/environmental conditions without the need for multiple finite element analysis for each condition but loses fidelity in identifying response peaks. Both approaches can be readily extended to other types of risers (shallow and deep water) and other subsea infrastructure (mooring lines, tendons) and a combination of these approaches can lend itself to capturing the fatigue response characteristic in conjunction with a minimalistic field riser monitoring system. A schematic of the analytical approach that can be used to assess the health of a riser system and provide guidance is shown in Figure 1.

The vision for the virtual sensor monitoring system described herein is to train it using a machine learning model, initially with finite element global riser analysis data, and subsequently with full scale field data from the riser in service. Data aggregation from a term- and deployment-limited monitoring system is employed to capture system specific response information. The data usage is maximized by training the machine learning model. This hybrid strategy results in low cost virtual sensors for the life of field monitoring. A schematic of this hybrid approach is shown in Figure 2.

Virtual sensors are assigned at locations of interest and are validated with riser global response data. Part of the FEA generated input data is used to train the virtual sensors. The remaining datasets are used for testing and validation. Sensitivities are carried out to assess the effect of data quality, training parameters and accuracy of fatigue predictions. A digital architecture for integration of virtual sensors to an on-board platform would provide the user interface to check the riser remaining fatigue life status.

Fatigue predictions (prognostics) from virtual sensors are compared against the fatigue damage calculated from design models. High fidelity results require careful selection of training datasets to represent riser response through the life of field. For instance, spectral characteristics associated with the free and forced vibration response of the riser system should be adequately represented by the digital model. In this paper, a proof-of-concept virtual sensor model is demonstrated for deployment of a low cost solution to life-of-field riser integrity management.
Fatigue Damage from FEA and Hybrid ANN/FEA Approaches

In global riser analysis, the fatigue damage rate for each seastate (Significant Wave Height (Hs)-Peak Period (Tp)-Direction combination) is calculated for every point along the riser length based on FEA simulations, either in the time or frequency domain. This model uses a mesh of 3D nonlinear beam elements. Analysis is typically conducted using irregular waves of 2 to 3 hours, either using response amplitude operators (RAOs) or motion time traces applied at the vessel, by solving the dynamic analysis problem:

\[ M\ddot{x}(t) + C\dot{x}(t) + Kx(t) = f(t) \]  

Eq. 1

where, \( M, C \) and \( K \) are the system mass, damping and stiffness matrices and \( \ddot{x}(t), \dot{x}(t), x(t) \) and \( f(t) \) are the nodal acceleration, nodal velocity, nodal displacement and external excitation force vectors. External excitation displacement and forces are typically from a combination of vessel motions, hydrodynamic loads from waves and currents on the riser, buoyancy and weights.

The fatigue life is accumulated based on the fatigue damage rate for each seastate and direction and factored by the associated seastate probability. A step-by-step breakdown of the process is shown in Figure 3.
In the time domain approach, stress time histories are obtained for each seastate along the riser. At each location, 8 circumferential points can be considered, as shown in Figure 3, and is calculated using:

\[
\sigma(t) = \frac{F(t)}{A} + \frac{M_y(t)c}{I}\cos\theta + \frac{M_z(t)c}{I}\sin\theta
\]

where, \( F \) is the axial force, \( M_y \) is the bending moment about the local y-axis, \( M_z \) is the bending moment about the local z-axis, \( A \) is the cross-sectional area, \( I \) is the cross-sectional moment of inertia, \( c \) is the radius out to the location where fatigue damage is to be checked and \( \theta \) is the angle of rotation counterclockwise from the local y-axis to the point of interest.

From the stress time traces, stress histograms are generated using the Rainflow cycle counting method, [15]. Here, fatigue damage is typically determined using the outer fiber stress on the pipe and the appropriate S-N curve for each location. The fatigue damage from each seastate is factored by the associated probability of occurrence and summed for each fatigue seastate and direction using the Miner-Palmgren rule, [16], to give the cumulative fatigue damage.

It can be computationally expensive to simulate a vast number of seastates for a complex nonlinear dynamic structural model. Statistical models that can optimize and match the targeted outputs based on an assumed set of inputs can reduce the need for a large number of computationally expensive FEA simulations. Artificial neural networks (ANN) provide an efficient approach for optimizing and identifying the nonlinear functional relationships that links the target parameters such as riser effective tension and two plane bending moments to the inputs (vessel motions), provided an underlying correlation exists.

ANN is a mathematical model based on the multilayer perceptron that is built on the structure and function of a biological neuron. The typical ANN architecture based on the multilayer perceptron approach consists of at least three layers: input, hidden and output layers, with the possibility of additional hidden layers that gives depth to the ANN. Each layer has neurons representing independent input variables and result parameters. Each pair of neurons is linked by connections and is represented by a combination of connection weights and bias parameters. An activation function is used to provide the computational properties of the neuron over a determined range of values for the weighted input and presents a form of binary behavior. A simplified approach would use the Heaviside function. However, this function is discontinuous and consequently alternative activation functions such as sigmoid, tangent hyperbolic and linear functions, [2], are preferred. The ANN model relating outputs to the inputs can then be written as:

\[
y(t) = \varphi_o \left( \sum_{k=1}^{M} \left( \varphi_h \left( \sum_{i=1}^{N} x_i w_{li}^i + b_1 \right) \right) w_{ok} + b_2 \right)
\]

where, \( N \) is the number of entries in the Input Layer, \( x_i \) are the inputs, \( w_{li}^i \) are the input connection weights, \( b_1 \) is the bias parameter, \( \varphi_h(.) \) is the activation function in the Hidden Layer, \( M \) is the number of entries in the Hidden Layer, \( w_{ok} \) are the hidden layer connection weights and \( \varphi_o(.) \) is the activation function in the Output Layer.

For time series data, ANN models based on recurrent neural networks (RNN) can take advantage of exogenous inputs.
(eX, vessel motions) and autoregressive (AR, outputs) data that represent present and past values (memory) to predict the target outputs using a nonlinear autoregressive exogenous (NARX) network. The NARX network is a dynamic network and requires data from both inputs and the parameters of interest (outputs). The input vessel motion and output riser loads are sourced from riser FEA simulations, effectively resulting in a hybrid FEA-ANN model. The trained ANN model is then tested with a number of sets of input seastate data from FEA to verify the efficacy of the algorithm across multiple seastates. In this approach, the role of FEA is supplanted by the trained ANN model to generate the load time traces, which are then post-processed to obtain fatigue damage rates at critical locations along the riser length. A graphical outline of the approach is shown in Figure 4.

![Figure 4 – Artificial Neural Network Structure (NARX) for Predicting Riser Loads from Vessel Motions](image)

Despite its efficiencies, there are limitations associated with using the NARX network model. When the correlations between motions and loads are harder to decipher, especially for riser locations near the mudline for a deep water riser, this can result in the need for a more complex network model. This can be in the form of an increase in the number of delays, neurons and hidden layers and simulation time to resolve the network and obtain an acceptable solution. Even then, there is no guarantee that a converged solution can be obtained.

An alternative approach is to develop a model based on a convolutional neural network (CNN). Typically, CNNs have been applied to imaging problems where object recognition and classification have supplied the motivation. However, research has shown that CNNs can be applied to multivariate time series for sequence classification, [17] [18]. While the problem at hand is not one of classification, the network can easily be adapted to support regression. A CNN works by decomposing the input into smaller chunks called feature maps. These feature maps then have a pooling kernel applied. The function of the pooling kernel is to smooth the data and reduce variance for the given feature map. These smoothed feature maps are then passed as input to the next convolution layer, creating more feature maps.

The feature maps represent unique patterns about the input that can be utilized for predicting what the overall image is or what the value of the next time step might be. On a standard image, a feature may be the curve of a human’s nose, the straight edge of a playing card or any other defining feature. For a time series based on the 6 degree of freedom (DOF) vessel motion inputs, a feature represents both the 6 DOF motions at a given time ($t_i$) and the orientations leading to and beyond that point ($S_n = \{x_1, ..., x_i, ..., x_n\}$). A graphical outline of the CNN approach is shown in Figure 5.

In order to match the target parameters/functions, the ANN has to be trained to obtain the optimal combination of weights and biases described in the hidden and output layers. This is done through an iterative approach with a progressive reduction in error between the ANN predicted output and target as the solver attempts to reach the minima (preferably a global minima) based on numerical equation solvers such as gradient descent, conjugate gradient, Newton’s method, quasi-Newton method such as damped least squares or modified stochastic gradient methods such as adaptive moment estimation (Adam), [19], and a defined loss function. The training process continues until the error/loss function meets an acceptable value. A popular loss function is the mean square error (MSE). The method popularly used to identify the preferred weights is Backpropagation. A schematic of the training process is shown in Figure 6.

There are several potential pitfalls in this training process. Solvers can be stuck in local minima or undershoot/overshoot the actual solution, with increasing complexity as the dimensionality of the problem increases. If too many parameters are used for training, there is potential for overfitting. The preferred strategy for identifying the optimal solution is to train with some portion of the data for training and the remaining for validation. This enables verification of the predictive capabilities of the ANN.
Case Study: Vertical Top Tensioned Riser
A vertical riser system consisting of a 21 inch drilling riser with a subsea BOP, deployed from a MODU in 5,000 ft water depth is used as a case study to develop the virtual sensor and assess their accuracy to measure riser fatigue damage using just platform motions as input. The riser and conductor system is modelled as an equivalent single string and includes the drilling riser, tensioner system, BOP and LMRP, wellhead and conductor modelled to 50m below the mudline. The riser system consists of slick and buoyant joints. The top of the drilling riser is terminated at the drill floor and the conductor-soil interaction is modeled using non-linear springs.

The net overpull at the base of the LMRP is approximately 450 kips, resulting in a top tension of 1,800 kips. The riser stackup and locations of interest (indicated by green asterisk symbol) are provided in the schematic provided in Figure 7. The three locations of interest include: telescopic joint, 5 ft pup below telescopic joint and termination joint above the lower flex joint.

The effect of wave loading is captured with the riser deployed from a representative MODU. The seastates provided in Figure 7 are modeled using JONSWAP spectrum (irregular wave) along two directions: head sea and quartering sea and are appropriately applied using the MODU response amplitude operators (RAOs), resulting in 6 degree of freedom (DOF) vessel motions. These include: heave, surge, sway, yaw, roll and pitch. A 2 hour simulation, sampled at 0.2 seconds, is analyzed in Flexcom, [14], and time traces are extracted for the 13 seastates in two directions. The ANN-FEA methodology is used to obtain training models for effective tension and the bending moment in two planes for all head sea and quartering sea seastates.
**Preliminary Data Review**

As a first step, the correlations between the vessel motions and riser loads are examined for two different seastates as shown in Figure 8 and Figure 9. The linear regression fit of each dataset relating the riser loads with the corresponding vessel motion DOF is highlighted using a solid black line. The results observed indicate that the effective tension at different points along the riser is strongly correlated with the vertical acceleration and the bending moments near the hang-off are strongly correlated with the pitch motions (z-rotations) and to a lesser extent with the surge motion (not shown). However, the bending moment near the mudline (at the transition joint above the lower flex joint, LFJ) are not strongly correlated to any of the vessel motion DOFs. While z-bending moment for seastate 3 appears to have only a slight correlation with the pitch motion (z-rotations), no such trend is even observed for seastate 10. This result suggests that except for the z-bending moment above the LFJ, the parametric relationship between the vessel motions and the riser force parameters can be easily derived using a suitable machine learning algorithm. The challenge here is primarily one of having a common algorithm across all seastates.

To examine this further, a CNN is used to classify the type of dataset for the head sea seastates. As shown in Figure 10, the CNN classifier has no difficulty in predicting seastates less than seastate 6, for bending moment loads at the transition joint above the LFJ. This is consistent with the previous observation that seastate 3 z-bending moment appears to have a slight correlation with the z-rotation. However, this result is not seen for higher seastates. In seastates 6-9, predicting the z-bending moment is more difficult and seastates 10-13 provide the lowest accuracy predictions.

This inability to resolve the seastates effectively suggests that external sources influence the nonlinearity of the problem. Typically, deep water risers have several external sources including hydrodynamic damping, BOP stack substructure excitation and soil conductor interaction that are not accounted for in the vessel motions. While the nonlinearities can confound effective classification and/or regression, the results obtained from the confusion matrix suggest the feasibility of using a limited number of seastates to build an ANN model. This is examined by considering two different ANN approaches: one approach is based on training using a limited number of seastate data and the other uses all available data.
Figure 8 – Bending Moment-z and Effective Tension for Seastate 3 (Head Sea)

Figure 9 – Bending Moment-z and Effective Tension for Seastate 10 (Head Sea)

Figure 10 – Confusion Matrix Density and Critical Seastates for Batching Sequences
Methodology
Training is carried out with a select number of seastates that includes information on the free and forced vibration response of the riser system. The objectives of the assessment are:

(a) Resolve the apparent lack of correlation between the vessel motion degrees of freedom and the bending moment at the transition joint above the LFJ; and,

(b) Obtain one algorithm for each load parameter at each location of interest across multiple seastates, inclusive of multiple directions. This is based on the assumption that wave direction information will not be available in the field and will be further obscured because of wave spreading.

The techniques used and the accuracy of the outputs obtained from the hybrid approach is estimated by comparing the loads and/or fatigue damage results with the corresponding values obtained from FEA. A schematic of the workflow adopted is shown in Figure 11.

Artificial Neural Network Methodology
Two approaches are used to demonstrate the efficacy of the hybrid ANN/FEA approach. The salient features and associated evaluation process for implementing the NARX and the CNN approaches are summarized in Table 1 and Table 2, respectively.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Detail</th>
</tr>
</thead>
<tbody>
<tr>
<td>Software Tools</td>
<td>MATLAB, associated Neural Networks, Statistical &amp; Signal Processing toolboxes</td>
</tr>
<tr>
<td>Data Normalization</td>
<td>$\hat{y}_n(t) = (y_n(t) - \mu(y_n(t))) / \sigma(y_n(t))$</td>
</tr>
</tbody>
</table>
| Optimization Algorithm         | Levenberg-Marquardt method (Damped Least Squares) with:  
1 hidden layer (shallow network), 10-20 neurons in hidden layer and 2-10 exogenous input and autoregressive feedback delays, depending on the parameter of interest |
| Weights Initialization         | Nguyen-Widrow algorithm                                                |
| Training Data                  | Training using sequential sampling with segments of a maximum of 3 seastates in 2 directions |
| Training Data Length           | 30% of the maximum length of each training seastate                   |
| Validation Data Length         | 10% of the maximum length of each training seastate                   |
| Testing Data                   | 100% of each seastate                                                 |
| Error/Loss Function            | Mean square error, $MSE = \frac{1}{N} \sum_{t=1}^{N} (y(t) - y'(t))^2$, where N is the number of data points, $y(t)$ is the output time trace and $y'(t)$ is the target time trace |
| Goodness-of-Fit Evaluation     | $R^2 = 1 - \frac{N \cdot MSE}{Variance\ (y'(t))}$                     |
| Data Renormalization           | $y(t) = \hat{y}(t) \sigma(y_n(t)) + \mu(y_n(t))$                      |
| Accuracy of Estimation         | Error Percentage = $100 \left( 1 - \frac{Fatigue\ Damage_{ANN/FEA}}{Fatigue\ Damage_{FEA}} \right)$ |

Table 1- Salient Features of Nonlinear Autoregressive eXogeneous Algorithm/Damped Least Squares Algorithm

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<table>
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<tr>
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<th>Detail</th>
</tr>
</thead>
<tbody>
<tr>
<td>Software Tools</td>
<td>Python and the associated neural network routines in Tensorflow and Tensorboard</td>
</tr>
<tr>
<td>Optimization Algorithm</td>
<td>Adaptive Moment estimation (Adam) with learning rate of 0.001, $\beta=0.9$, $\beta_2=0.999$ and $\epsilon=10^{-8}$ Four convolution layers and four pooling layers used sequentially (deep network)</td>
</tr>
<tr>
<td>Training Data</td>
<td>Training done using random mini-batch sampling across all seastates with the following split:</td>
</tr>
<tr>
<td>Mini-batch window</td>
<td>512 data points (102.4 second time trace)</td>
</tr>
<tr>
<td>Training Data Length</td>
<td>First 90% of the maximum length of each training seastate (all 26 seastates used for training)</td>
</tr>
<tr>
<td>Testing Data</td>
<td>Last 10% of each seastate</td>
</tr>
<tr>
<td>Error/Loss Function</td>
<td>Mean square error, $MSE = \frac{1}{N}\sum_{i=1}^{N}(y(t) - y'(t))^2$, where N is the number of data points, $y(t)$ is the output time trace and $y'(t)$ is the target time trace</td>
</tr>
<tr>
<td>Goodness-of-Fit Evaluation</td>
<td>$abs\left(\frac{y(t) - y'(t)}{y'(t)}\right)$</td>
</tr>
<tr>
<td>Accuracy of Estimation</td>
<td>$Error\ Percentage = 100 \left(1 - \frac{Fatigue\ Damage_{ANN/FEA}}{Fatigue\ Damage_{FEA}}\right)$</td>
</tr>
</tbody>
</table>

**Table 2- Salient Features of Convolutional Neural Network/Adaptive Moment Estimation Algorithm**

**Analysis Results**

A snapshot of 250 seconds (out of a total snapshot of 720 seconds – 10% of total time trace length) comparing the effective tension, bending moment-y and bending moment-z above the LFJ, using the three different approaches, for seastates 3 and 6 (quartering sea) is shown in Figure 12 and seastates 8 and 10 (quartering sea) is shown in Figure 13. A single NARX and a single CNN model is used for all 26 seastates, in both head and quartering sea directions to generate the time trace data.

![Figure 12](image-url)

*Figure 12 – Time Snapshots at the Transition Joint above the LFJ of Effective Tension (Teff), Bending Moment-y (My) and Bending Moment-z (Mz) for Seastates 3 and 6 comparing NARX, CNN and FEA*
The results in Figure 12 and Figure 13 show that the effective tension using the NARX approach matches the effective tension using the FEA approach at the lower flex joint location, for both low and high seastates with error rates less than 5% for seastates 6, 8 and 10. However, higher errors in effective tension are observed for seastate 3 (more than 10%). Also, the NARX approach shows a lower degree of match for the associated bending moments. This is especially seen for the lower seastates (quartering seastate 3 and to some extent for seastate 6) while a much better match is observed for the bending moments at the higher seastates (quartering seastates 8 and 10). The CNN approach does not have this issue and matches the bending moment results obtained from FEA with error rates less than 5%. The NARX approach matches the effective tension and bending moments near the top of the vertical riser for both low and high seastates with error rates less than 5% across all head and quartering sea seastates (not shown in this paper). Hence, the NARX approach is adopted for the upper riser locations based on its acceptable accuracy levels across all seastates and speed of development. The CNN approach is adopted at the LFJ location as it provides the required levels of accuracy unlike the NARX approach.

**Analysis Results: Fatigue Damage**

The time trace trends are also reflected in the fatigue damage results for head and quartering sea seastates shown in Figure 14 (comparison of fatigue damage rates) and Figure 15 (comparison of errors as defined in Table 1 and Table 2). The maximum error in fatigue damage rates for data extracted at the telescopic joint and at the 5 ft pup below the telescopic joint between FEA and hybrid FEA/NARX approaches is typically less than 10%. These results represent a high fidelity match. However, the fatigue damage rate results using NARX for the location near the bottom of the riser (above LFJ) do not show a good match over seastates 1-5 (quartering seas) and seastate 1 (head seas).

To alleviate this large error, bending moment time traces are extracted using the FEA/CNN model. A comparison of the fatigue damage using this revised approach is shown in Figure 16 for all head and quartering sea seastates and shows an improved match across all seastates. Note that the results shown are based on only the last 10% of the time trace because the first 90% of the time trace is used to obtain the feature maps from the CNN model. The results obtained show that it is
feasible to reduce the fatigue damage error using alternative neural network models such as the CNN model and bring it down to an acceptable level of error (below 30%) compared to the FEA results.

To verify the robustness of this approach, analysis is conducted with 100% of a test seastate (Hs=2.75 m, Tp=8.0 seconds) and the results are compared with a FEA result above the LFJ as shown in Figure 17. The results obtained show that the trends obtained for the test seastate are acceptable and consistent with those obtained for seastates 5 and 6 that are closest in Hs/Tp values and the error in fatigue damage rates is less than 20% for both head and quartering sea test seastates.

Figure 14 – Fatigue Damage Rate Comparison – NARX vs. FEA – Head and Quartering Seas using single algorithm for Quartering and Head Seas

Figure 15 – Fatigue Damage Rate Errors – NARX vs. FEA – Head and Quartering Seas using single algorithm for Quartering and Head Seas
Figure 16 – Fatigue Damage Rate and Error Comparison – At Termination Joint, Above LFJ for Head and Quartering Sea Seastates

Figure 17 – Fatigue Damage Rate and Error Comparison – At Termination Joint, Above LFJ for Head and Quartering Sea Seastates – Blind Time Trace Robustness Check – $H_s = 2.75 \text{ m}, T_p = 8 \text{ seconds}$.

Summary and Conclusions
This paper presents a hybrid ANN/FEA approach to determine the response of a deep water riser in 5,000ft water depth. The feasibility of the hybrid approach is demonstrated through a case study involving a vertical riser (low pressure drilling riser). The results presented demonstrate the fatigue damage prediction accuracy of using trained ANN models at various critical locations on a drilling riser and include challenging regions such as the lower flex joint. Furthermore, the results show the need for developing different ANN models (NARX and CNN) to address more complex non-linear problems.

This methodology can also be extended to other forms of riser and subsea systems. Adaptive training can also be developed and can include a hybrid measurement/ANN approach or a hybrid measurement/FEA/ANN approach. Here, field data measurements from subsea sensors on the riser can be used to either obtain a trained ANN model or supplement a FEA-ANN hybrid model by incorporating adaptive training. It is in this context that the ANN model is referred to as a virtual sensor. This approach can then be used for monitoring of riser systems by combining it with a minimalistic term-limited monitoring system. The primary benefit of this approach is that it keeps cost down by extending the results of the monitoring system to all the risers deployed from a platform. This approach also feeds into integrity management fitness-for-purpose assessments, life extension analysis and improving future design practice.

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Nomenclature

3D = Three dimensional
Adam = Adaptive Moment (estimation)
ANN = Artificial Neural Network
BOP = Blowout Preventer
CNN = Convolutional Neural Network
DOF = Degree Of Freedom
FoS = Factor of Safety
FPS = Floating Platform System
FPSO = Floating Production, Storage and Offloading Vessel
JONSWAP = Joint North Sea Wave Project
Jt. = Joint
LM = Levenberg-Marquardt
LMRP = Lower Marine Riser Package
MODU = Mobile Offshore Drilling Unit
NARX = Nonlinear Autoregressive eXogenous
RAO = Response Amplitude Operator
RNN = Recurrent Neural Network
SCR = Steel Catenary Riser
TLP = Tension Leg Platform
VIV = Vortex Induced Vibration

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