Application of Artificial Neural Network on Health Monitoring of Offshore Mooring System

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Abstract. The amount of floating offshore structures had been grown rapidly over these few years due to deepwater exploration and production activities, and this increase in number is predicted to remain over the coming years. Due to the catastrophic consequences from offshore mooring system failure and the limitation on the traditional method for failure detection, there is a need for alternative methods for health monitoring of the offshore mooring system. Artificial Intelligence (AI) has acquired recognition in these few years for petroleum engineering approach, especially Artificial Neural Network (ANN) thanks to its potential to solve complex problems with less time-consuming and effort. A review of the application of ANNs on health monitoring of offshore mooring system had been presented in this paper. The ANNs system had demonstrated its capability as a health monitoring tool for offshore floating structures to detect any damaged or broken mooring system.

1. Introduction

Due to the deepwater environment, the traditional fixed offshore structures had been unsuitable to be use. Thus, possible offshore platforms ideas had been introduced, such as Tension Leg Platform (TLPs), semisubmersibles, spars and Floating Production Storage and Offloading Systems (FPSOs) [1]. As the number of floating platforms keeps growing, there is also a related growth in the number of aging floating platforms, which some are approaching or over their initial design lives.

In the petroleum industry, mooring line is an important aspect for floating platforms [2]. Maintaining a stable position in the sea enables the facilities to have a continuous production or operation. Without a reasonably stable position well drilling and transportation of hydrocarbons from the reservoir to the surface would not be possible. The offshore mooring systems generally consisted of lines, connectors, tensioning instrument, and anchors. The restoring force generated by the mooring system will offset the environment and operational loads of the floating platform. The mooring system can be designed for broad scale of water depths, which can be from a few meters to over 3000m [2].

However, in these few years there have been several cases which the deepwater mooring system had failed during its operation. These malfunctions mostly caused by fatigue, corrosion, weathering, flaws in manufacturing, damage throughout installation etc [3]. Several events happened during the last decade had been documented and presented [4-5]. There were at least 23 incidents of failure related to the mooring system have been recorded, and 4 of them have been disastrous [4]. The number and the severity of these incidents have raised concern among the owners, operators, and engineers.

Moreover, the increase in the number of failures happened in floating production systems is proportional to the increased use of FPSOs [6]. Huge number of failures have been associated to
various reasons, such as design, quality control of material, installation, and inspection/maintenance. Although these malfunctions had caused a consequential safety, labouring and environmental cost, it can be prevented by using monitoring technique incorporated with an integrity evaluation, fatigue damage calculation tools and models for forecasting the dynamic responses of the floating platform and its mooring lines.

Structural Health Monitoring (SHM) is a discipline that focuses on recognizing damage in a specific structure. This technique usually detects the damage caused by the growth of fatigue cracks and the deterioration of structural connection [7]. This technique is planned to give a verification of the condition of the components, of various sections, and of the complete congregation of these components’ contribution to the structure during its entire lifespan. The significance of sustaining the structural integrity of mooring system is well acknowledged, and the structure examination is important for showing the current structural integrity and its possibilities for life extension. Structural integrity monitoring of mooring systems can be accompanied with existing examination methods to give substantial trust in structural integrity, or to decrease the cost of inspection. Watch circles and line tension measurement sensors are conventional methods for detecting any mooring line failure [8]. However, the water circle method is highly dependent on the information about the environmental conditions, and the line tension measurement sensors are hard to preserve. Therefore, a robust method for the health monitoring of mooring system should be developed.

Due to the current growth on the field on Artificial Intelligence (AI), there is an increased interest by petroleum industry to use Machine Learning (ML) for applications such as irregularity detection, structural integrity assessment, virtual sensors etc [9-10]. AI is the capability of the computer system to imitate human intelligence in managing different works such as training, inference, self-correction etc [11]. AI is capable to receive vast amount of data, rapidly organize those data, conduct analysis, and provide the desired output. AI has played an important part in the petroleum industry ranging from the understanding of geological information, to the actual production of oil and gas. Artificial Neural Network (ANN) is one of the familiar applications from artificial intelligence.

2. Artificial Neural Network

2.1. Background

The initial neural network research was performed in 1943 by McCulloch and Pitts [12]. It is one of the techniques that adapted the Machine Learning (ML) algorithms, which was evolved on an idea of resembling the neural system in human brain. According to Mohaghegh, Artificial Neural Network (ANN) is a data organizing system that had a precise operation attribute which is similar to biological neural network [13]. The nerve impulses or electrochemical signals will be processed in individual neuron cell, whereas the human brain which is a complex neuron network which will transmit the data with the assistance from different interlinked neurons [14]. A particular biological neuron will be made up of an axon, a cell body, and dendrites. Figure 1 showed the schematic of artificial neuron.

ANN is a simulation for the biological process stated above [15]. Some presumptions are being considered when constructing an ANN based on mathematical models [13]. First, the information processing happens in numerous simple elements named neurons (processing elements). Next, the information is proceeding between neurons through connecting links. A corresponding weight will be assigned to each connecting link. After the neurons received the input, the neurons will execute an activation function and calculate its output.
After the product from other neurons had been multiplied with the weight of the connecting link, it will enter the neuron as the inputs. All the inputs are aggregated, and activation function of the neurons will be implemented to determine the output. A neuron may consist of multiple inputs but only one output. Only one input layer and one output layer will exist in an ANN, but the number of hidden layers can be one or more. The hidden layer is important for expressing the traits from the data [13]. An example of three-layer neuron network is showed in Figure 2.

2.2. Methodology of constructing ANNs
According to their training methods, the neural networks can be separated into 2 vital classification, which are supervised and unsupervised. Unsupervised neural networks do not have feedback provided to the network and they are mostly for assembling and categorization algorithms. The input vectors will be classified and clusters, and each cluster will consist of a group of several weights. Almost all the neural network implementations in the petroleum industry are supervised training algorithms build. For this training methods, both input and output are introduced to the network to allow the machine learning on a feedback basis [13]. For this section, the supervised training algorithms will be the focus.

2.2.1. Data selection and collection for input
There are a few methods that can be applied for selecting the inputs, such as modelling, experiment testing, simulation, sensitivity analysis, specialist judgement, statistical interpretation etc [15]. After the type of input data had been chosen, the data collection will be conducted. For supervised training algorithms, both the inputs and outputs should be obtained for neural network.

2.2.2. Selection of training, testing and verification data
After the data had been collected, the data will be separated into three segments, which are training, testing and verification group [16]. The ANN model will be constructed using the training data. To modify the weights for every input, the targeted result is being utilized to assist the network. The error from the output will backpropagate in the neural network and modify the weights of the inputs through the calibration is achieved. This method is named as “feedforward backpropagation algorithms”. To compute the network generalization, the testing data will be utilized, and the training process will be ended when the generalization is ceased from tweaking [17]. Lastly, the verification data will be used to access the capabilities of the network.

2.2.3. Data normalization
If the value of the inputs or outputs are too small or too large, the data scaling will be carried out [18-19]. One idea of normalizing data had been demonstrated by Demuth et al. [13]. The normalizing data will be having the numbers ranging from -1 to 1.
\[ X_i' = 2 \left( \frac{x_i - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \right) - 1 \]  

(1)

Where \( X_i \) is the initial amount of the variable, \( X_i' \) is the normalized amount of \( X_i \), \( X_{\text{max}} \) and \( X_{\text{min}} \) are the highest and lowest amount of \( X_i \).

2.2.4. Calculating the number of hidden layers and training function

Iteration should be conducted to calculate the ideal number of hidden layers and the number of neurons in each hidden layer, until the ideal number of hidden layers is obtained [15]. The total average absolute deviation (TAAD) or mean square of error (MSE) should be determined, starting with one neuron until reaching a number of neurons which have the least error. The training function should be chosen after the ideal number of hidden layers and the number of neurons in each hidden layer is being estimated so that the error is reduced. The example of training function that can be tested are [15]:

- “Variable Learning Rate Backpropagation” (GDX)
- “Resilient Backpropagation” (RP)
- “Fletcher-Powell Conjugate Gradient” (CGF)
- “Scaled Conjugate Gradient” (SCG)
- “Levenberg-Marquardt” (LM)
- “Levenberg-Marquardt with Bayesian Regularization” (BR)
- “Quasi-Newton” (BFG)
- “One Step Secant” (OS)

3. Application of ANN on health monitoring of offshore mooring system

ANNS have been applied to solve many complex issues in petroleum industry. The application of ANNs for the health monitoring of offshore floating structures and its mooring system will be discussed in this section.

For turret-moored FPSO, Mazaheri et al. had developed the ANN modelling technique to forecast the FPSO’s responses when acted on random wave, wind and current loads [20]. The author affirmed that it was not feasible to conduct a full simulation for the dynamic response of FPSO for each 3-hour interval of environmental statistics. Thus, the ANN technique is used for the analysis. The results showed that there was a great saving of time for the analysis even considering the process to train the ANN system. The author concluded that the ANN system had successfully predict the vessel’s response and the model can be a feasible substitution for response-based technology method to estimate the dynamic response of the vessel over its service lifetime.

For spar platforms, Uddin et al. had implemented ANN model for forecasting the dynamic response of spar mooring line [21]. The author mentioned that the Finite Element Method (FEM) takes a lot of time to process and it is said to be computationally expensive. Therefore, ANN model was introduced as an alternative for analysis as the computational efforts required to forecast the dynamic response of spar mooring line was considered very little when compared to full FEM simulation. The feedforward with backpropagation training algorithms was used as the training algorithms for this ANN model.

Next, Christiansen et al. had proved that ANN can be instructed to calculate the tension forces existed in a mooring line [22]. Even for the sea states that are not evaluate in the training input, the ANN still could solve a huge scope of various sea states by substitute the suitable training input. However, the author stated that weighting of the error function that are utilized to instruct an ANN to highlight the tip response did not enhance the performance of ANN regarding the precision of fatigue assessment. The proposal of weighted error function had proved to decrease the general capability of an ANN system. In his work, the network optimization is not taking into consideration, but it will be a concern for the future work.

To design and analysis floating production system more efficiently, Pina et al. had associated the ANNs and wavelet networks (WN) with the coupled methodology, which will provide precise results for the response of the floating structure and its mooring lines [23]. The author stated that this method
had exceptionally reduced the processing time for the analysis. The author further explained that for optimization processes, the proposed models which could provide swift results while preserving acceptable accuracy will be an interesting choice for the analysis, as thousands of different solutions were required to be tested for the optimization process. For more systematic and reasonable arrangement of the mooring systems, the ANN models also could be used during the initial or intermediate design stages. The development of ANN for the analysis of spread mooring arrangement of floating vessels also had been conducted by Pina et al. [24]. The ANNs had provided precise data for responses of the floating vessels that were needed for outlining the mooring systems. The author stated that this method can be used for predicting more structured and reasonable arrangements for the mooring systems and risers, and important elements for offshore oil exploitation systems.

Yetkin et al. had used ANN model for optimization of 4-point tanker-buoy mooring system [25]. The ANN model had been used for 1000 various states and the ANN model had successfully calculate the ideal tanker-buoy mooring system which had least tensions for every mooring line and motion movement. The author stated that it was easier to determine the tensions and the motion movements of spread mooring systems for various environmental condition by utilizing ANN model when compared to numerical simulation.

To calculate the fatigue damage on the mooring systems of floating offshore wind turbine, Chun et al. had used the technique of applying multilayer feedforward (MLFF) ANN with backpropagation (BP) training strategy [26]. Regarding to the tension range distributions, the well-trained ANN had displayed good outcome for the time domain analysis. As conclusion, the author stated that the ANN can be utilized to estimate the wide-banded fatigue damage in offshore structures. In his study, 121 attributes were utilized as output neurons to display the tension range distribution, and these huge amounts of output demanded a longer training time. Therefore, appropriate variable as input and output neurons needed to be select for future work.

Gumley et al. had presented the method of predicting the motion of the single point moored FPSO by using neural network [9]. The author stated that this method is a dedicated estimation for detecting any changes in the mooring system, and eventually can be presented as the early detection of a mooring line failure. The author further stated that the neural network method is preferably suitable for the floating platforms that had already be installed in the oil field, as compared to other health monitoring method which are undependable or costly to retrofit. However, the author expressed that there is limitation in the use of the neural network model depending on the parameters that were provided for modelling, as every different floating platform was influenced differently by the environmental loads and conditions. Therefore, the model was required to recalibrated if the input variable did not give accurate results.

Sidarta et al. had used ANN to forecast the tension in mooring line of the Heave and VIM suppressed (HVS) semi-submersible [27]. The results by the ANN system were having high accuracy when compared to the result of numerical simulations. The ANN model had successfully forecast the tensions in the mooring system for multiple sea states with various significant wave height (Hs) and wave peak periods (Tp), which could be used for fatigue analysis of the mooring lines. His study had proved that the ANN system had a significant possibility for the monitoring of dynamic response of floating systems and predict for any failure before they occur. The research was further improvising by Sidarta et al. to diagnosis and recognize a damaged mooring line by using ANN model [28]. The ANN model is trained to detect the variant in the long drift period of the floating structure, which is an outcome of vessel offset and total mass. This method was reckoned as pattern recognition and classification complication, which neural network is excellent in solving this problem. This research had again demonstrating the great potential of ANN model as a health monitoring system to provide warning by detecting damaged or failure.

Furthermore, Sidarta et al. had demonstrated the use of ANN model to recognize a fractured mooring line in a spread-moored FPSO and determine which group of mooring lines that consisted the fractured line [29]. The ANN model is trained to capture the deviations in the low-frequency periods and mean yaw angle of the floating structure as an outcome of position, mass and added mass of the floating structure. This ANN model used a backpropagation training algorithm and a preprogrammed technique for calculating the dimensions of hidden layers in ANN system. To further enhance the
ANN model, the author also stated that the net mean roll angle also could be utilized. The variance between measured statistics and the results from numerical simulations will be investigated in the future work. To increase the reliable of the ANN model, the real time reconditioning of the ANN system using actual real dynamic response of the vessel also could be conducted.

For damage detection of offshore mooring lines, Aqdam et al. had proposed to use Radial Basis Function (RBF) neural network [30]. RBF networks is one type of ANN which had added precise output than the vector inner product which is utilized in other ANNs. His work was concentrated on the modeling and recognition of mooring system by assessing the repercussions of unpredictability in the modeling. The low and moderate defects could be diagnosed by the proposed RBF and it was capable to understand the non-linear performance of the structure. The modeling and the detection techniques were endorsed through experiment studies, and the result stated that the proposed RBF was more favorable when compared to other methods. In his work, the motion of the floating structure was considered as uncertainties and irregular waves were not assessed in his study.

Most of the papers had demonstrated the capability of the ANN model to forecast the dynamic motions of the offshore floating structures and its mooring system. The main advantages of using this method would be less time-consuming and easier to conduct the full examination of the floating vessels and their mooring system [31]. Initially, the ANNs system are utilized to predict the dynamic responses and the performance of different vessels in different metocean condition. As the ANN method can be used to capture the variation in the historical data and to detect for damaged or failure of the system, these factors have led to the application of ANN method for the health monitoring of mooring system to detect any anomaly or failure based on historical records [28-30]. However, each ANN model is unique for each different environment loading and the structural data [27]. Therefore, the input variables such as the environmental condition and the structure data for the ANN model must be calibrated from time to time to ensure the desired output will be much similar with the real output. The real-time response data of the floating platforms also can be utilized to improve the reliability and the precision of the ANN model.

4. Conclusion
The various application of ANNs on the health monitoring of offshore mooring system are presented in this work. ANN had proved to be a practical technique for conducting the dynamic analysis of offshore mooring system and as a monitoring system to provide early warning by detecting variance from historical records and to recognize for any damaged or failure of mooring system. The system can be improved further by implementing real world analysis data.

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