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MONITORING MOORING (MONIMOOR) LINES OF FLOATING STRUCTURES USING DEEP LEARNING-BASED APPROACHES

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Abstract. *The renewable energy sector, specifically offshore wind energy, has grown rapidly in Europe in recent years, owing to the lower energy costs. A typical Floating Offshore Wind Turbine (FOWT) system is comprised of several coupled subsystems that should jointly ensure its integrity under nominal operating conditions as well as sustainability under extreme conditions or prolonged usage. From the reliability perspective, one of the most critical subsystems is the mooring system, which keeps the platform floating in a stable condition. Eventually, monitoring the mooring lines is important to ensure the safety and serviceability of FOWT throughout its service life. This article describes a comprehensive model for assisting businesses in planning real-time monitoring of the FOWT. The proposal combines an Auto-regressive model (AR) with a Convolutional neural network (CNN) in a near real-time approach for damage detection in FOWT. The CNN-based approach monitors and subsequently identifies anomalies in the AR model coefficients of the motion prediction model apriori trained for the FOWT platform under its undamaged condition.*

Accordingly, a model to predict the motion of a semi-submersible FOWT platform is prepared to employ undamaged time history response (single point displacements and rotations) and the optimal AR coefficients are identified under all sea states and damage conditions. The proposed deep learning-based CNN is further employed to attribute these coefficients to different damage/health states of the platform. The effectiveness of the proposed approach is validated through numerical simulations using NREL's open-source wind turbine simulation tool Open-FAST. In the numerical model, various scenarios are simulated in an attempt to replicate real damage scenarios under varying metocean conditions while taking into account the plausible failure mechanisms in the mooring lines. The strategy of combining AR and CNN in a novelty detection-based methodology performs admirably in damage identification and classification.

Keywords: Structural health monitoring; Offshore Structures; Damage diagnosis; Mooring lines; Auto regressive Model (AR); Convolutional Neural Network (CNN).

1   Introduction

Supported by the strong surge in industries dealing with offshore wind energy, the research on the performance and sustainability of such structures has taken a significant leap. Maintaining such structures within the required safety and serviceability envelopes and ensuring optimal maintenance cost has been a major point of concern over the last few decades. In this regard, industrial applications have always emphasized the cost (installation and maintenance) aspect of Structural Health Monitoring (SHM) techniques with respect to the benefits achieved and significant research has been undertaken in this domain.

One of the key reasons structural health monitoring (SHM) approaches are adopted in various industrial sectors is cost optimization. It has been perceived that adopting data-driven methodologies to detect structural degradation can greatly lower uncertainty in the offshore oil and gas industries [1]. Data-driven approaches belong to the family of inverse problems and have been successfully employed for the solution of structural and mechanical problems. Such approaches take the basis of the concept of inference of material properties by an analysis of indirect measurements. Typical inverse problems could be challenging to solve since a certain set of measurements could correspond to various sets of material or operating conditions, leading to confusion in the decision-making process.

Thankfully, with high-level ML-based approaches, complexity with such inverse problems has been successfully alleviated, leading to superior reliability and predictability for a very wide band of application areas. The recent surge in the application of such algorithms for damage detection in bridges [2], onshore wind structures [3], or multiple applications in bio-sciences corroborate the same. Nonetheless, the research on fault detection in offshore systems and especially for offshore wind structures, such inverse problems solutions are yet to achieve the desired maturity. This is due to the fact that the industry is still in its infancy and consequently, the available data sets are limited. Fortunately, a conceptual framework for such data-driven approaches [4] for the operation of wind farms has recently been implemented successfully using the concept of digital twin (instead of the real structure), targeting improvement in future design and increasing the reliability of the offshore wind platforms.

Researchers are nowadays implementing deep learning algorithms to detect damages in components for wind systems [5, 6]. The mooring line is one such subsystem that is perceived to be very crucial for the overall integrity of the floating offshore wind turbine (FOWT) structures. Recently, various studies have investigated the economic feasibility of the FOWT systems by optimizing the design of support structures and mooring systems [7, 8]. Understanding the aero-hydro-elastic-mooring coupled dynamic response of the FOWT is important to ensure its safety under extreme wave and/or wind loading. Further studies identified the substantial impact of damage in the mooring line on the dynamics and stability of the whole system. This has drawn significant attention from the SHM researchers to monitor the mooring system in the FOWT [9] to ensure overall safety. Further, the dynamic response of a submerged FOWT with different configurations has been studied in [5] to assess its impact on the whole systems under normal and extreme sea states. [10] simulated the offshore code comparison collaboration continuation (OC4) DeepCWind semi-submersible FOWT model in order to investigate the impact of wind turbine aerodynamics on the behaviour of floating platforms and mooring systems. Later, [11]'s study identifies the dependence of the weight of the mooring system for a tri-floater FOWT on the mooring line configuration.

Clearly, mooring lines have been identified to play a crucial role in ensuring structural stability in wind turbines, floating vessels, tension leg platforms (for oil and gas), etc. The damage in

mooring is further parameterized through aspects like fatigue rate analysis [12], fatigue damage [13], strength capacity [14], tension and durability [15], failure risk under extended environmental loads [16] etc. Beyond these, there are other failure modes for mooring which also need emphasis. In this attempt, recent researches focused on a Fuzzy logic-based damage diagnosis [17, 18, 19].

Contrastingly, an insignificant number of researches have considered data-driven machine learning or deep learning approaches for monitoring the health of FOWT mooring lines targeting early detection of failures. ML, while recently abundantly employed for complex problem solving, its unique benefits of achieving model-agnostic noise-robust unbiased estimate has not been exploited to that extent for FOWT health estimation till date. Clearly, this opens up a research path to develop ML-based algorithm for complex FOWT subsystems. Without any doubt, the importance of the mooring line on the overall system dynamics is significant, yet being only a subsystem of an entire FOWT, it can be better monitored while being dealt with lesser information. As proof of this concept, [20]'s research can be referred to wherein a simple fully-connected deep neural network detects the possibility of severe bio-fouling failure in the mooring systems inferring from the displacement and rotation information. This article, in particular, has introduced the novel approach of analyzing the displacement response employing deep neural networks in order to monitor FOWT health. With a similar objective, [21] employed artificial neural networks investigating its localization and classification efficacy for different damage cases.

Vibration or displacement-based damage diagnosis has been successfully employed for monitoring the health of mechanical systems from different fields: civil, mechanical, aero, naval, and offshore structures [22, 23, 24]. Such approaches employ model-based/-independent techniques to analyze operational, structural responses in order to locate and isolate the anomalies that occurred. Usual approaches have been to extract certain damage-sensitive features (DSF) in the time or modal domain. While typical of such DSFs have been the modal properties, time domain responses, their damage sensitivity has always remained the source of concern.

As an alternative, [25] presented coefficients of AR models as the suitable DSF that shows significant sensitivity on the introduction of practical levels of damage. [23] exploited initial three-order AR model coefficients as DSFs, and t-test has been used for the estimation of damage characteristics. [24] employed Gaussian mixture models for ARM coefficients and further damage was detected based on the number of models used. Employing ARM coefficients as DSFs in a data-based estimation environment for damage detection can be undertaken in either an unsupervised or supervised approach. With an unsupervised approach, novelty detection has been the most employed approach wherein the novelty on a predefined DSF is attributed to plausible damage scenarios. Statistical methods are further used to exploit the information stored in the novelty index [26, 27]. Nevertheless, unsupervised learning techniques are limited to damage detection only, while they struggle to localize and quantify the damage. On the contrary, supervised learning techniques can in actual go beyond detection [28], while demanding rich archive of input-output data that either has to be sampled from the system or simulated from a replicative support model. With data not being a problem for many structure types, supervised algorithm gained popularity over time.

Supervised algorithms can either be used as a classifier or regressor, depending on the network architecture. Both of these needs extensive training that has been typically approached using random forest, support vector machine (SVM), multi-layer perceptron (MLP), or other machine learning algorithms. Finally, with regard to damage detection in a structural system, the problem boils down to training such a network with suitable DSFs extracted from the re-

sponse against their corresponding damage labels in order to be able to predict the damage label from the DSFs. The extraction of features through trial and error may however have a subpar prediction effect since the coefficients of the different orders of the AR model have variable anti-noise abilities and sensitivities [29]. Also, this can lead to a process that is time-consuming and labor-intensive. Eventually, choosing suitable DSFs, in this regard, becomes imperative to ensure promptness and accuracy.

The current study addresses a similar problem, although emphasizing only on the mooring line damage, assuming it to be the only failure-prone zone in a FOWT. The investigation employs CNN to extract damage-sensitive features from the coefficients of Auto-Regressive Models (ARM) in an attempt to identify and classify damages. Research in this field has experienced that, with ML-based approaches, the major source of complexity originates from the proper selection of damage-sensitive features. While CNN is an excellent approach to classify any signal, yet the automated selection of damage features is at times cost intensive, especially when the signal is high-dimensional and/or of poor quality due to substantial noise contamination, FOWTs being one such example.

This article attempts to alleviate these issues through supplying cleaner and more feature-rich inputs to CNN. In doing so, AR models of the raw signal are first prepared targeting attenuating the ill impacts of noise and subsequently extracting ARMCs as the information-rich features that can be better trained with CNN. Eventually, this approach has to be trained for several damage cases and metocean conditions and ARMCs against each of the cases are to be labeled accordingly. Following, the CNN network needs to be trained with an ARMC-label dataset in order to be able to detect damage cases from ARMCs extracted from any arbitrary signals.

2 Methodology

Generally, structural response under ambient vibration conditions can be observed as a sequence of stochastic variables. As per the [30], an AR model can be used to represent such a process provided the sequence satisfies the condition of stationarity. Eventually, prior to modelling a sequence with AR modelling approach, it is advisable to remove the trend and further employ normalization to circumvent the ill-effects amplitude. This way, the sequence can be freed from the influence of the test environment and the load, which can be accomplished as:

$$\mathbf{x}(t) = \frac{\tilde{\mathbf{x}}(t) - \mu}{\sigma} \tag{1}$$

with, μ and σ denoting the sample mean and sample standard deviations of the raw signal $\tilde{\mathbf{x}}(t)$ while $\mathbf{x}(t)$ being the normalized data. AR modelling of an arbitrary order p can further be employed on this data as:

$$\mathbf{x}(t) = \sum_{i=1}^{p} \phi_i \mathbf{x}_{t-i} + e_t \tag{2}$$

where, $\{\phi_i\}, i = \{1, 2, \cdots, p\})$ are the parameters of the model and e_t is the white noise that needs to be estimated. Following, three processes are typically involved in AR modeling i.e. establishing the model's hierarchy, estimating its parameters, and subsequently assessing the model's applicability.

In order to decide the model order it is advisable to estimate the partial autocorrelation function (PACF) of the time series data. This way, the dependence of any entry in the sequence to its predecessors. Accordingly, the model order is selected till the auto-correlation function is

found to be substantial. To this cause, the sample auto-correlation function (ACF) r_j is typically estimated for a lag of j as,

$$r_j = \frac{\sum_{i=j+1}^{n} \mathbf{x}(t)\mathbf{x}(t-j)}{\sum_{t=1}^{n} \mathbf{x}(t)^2}, j = 1, 2, \cdots \tag{3}$$

Using these ACFS, the PACFs ($\hat{\varphi}_{j,k}$) are estimated as,

$$\hat{\varphi}_{jj} = \frac{r_j - \sum_{k=1}^{j-1} \hat{\varphi}_{j-1,k} r_{j-k}}{1 - \sum_{k=1}^{j-1} \hat{\varphi}_{j-1,k} r_k} \tag{4}$$

with,

$$\hat{\varphi}_{j,k} = \hat{\varphi}_{j-1,k} - \hat{\varphi}_{jj}\hat{\varphi}_{j-1,k-1}, k = 1, 2, \cdots, j-1 \tag{5}$$

Overall, this process helps in gaining a general understanding of the AR model's order range i.e. when likely φ_j equals $\hat{\varphi}_{jj}$. Then, using Equation 3, the coefficients of the AR model for various model orders. The variance $\hat{\sigma}_e^2$ of the residual e_t, can be calculated using sample variance of the time series, i.e., σ^2 as:

$$\hat{\sigma}_e^2 = \left(1 - \sum_{i=1}^{p} \hat{\phi}_i r_i\right) \sigma^2 \tag{6}$$

Eventually, this procedure can be repeated for various model orders. Finally, the optimum model order p can be suitably chosen taking the basis of Akaike's information criterion (AIC), detailed in the following,

$$\text{AIC}(p) = \ln\left(\hat{\sigma}_e^2\right) + 2(p+1)/s \tag{7}$$

with, s being the size of the time series data.

Eventually, accuracy in the estimated model is supposed to ensure stationarity and whiteness in the estimated residual. Among the several available methods for analyzing the residual's normality, the quantile-quantile (Q-Q) map is used in this study. By characteristics, the Q-Q plot tends to be resembling a straight line for stationary white Gaussian noise processes.

Accordingly, the suitable model order is chosen through the process described above. The model coefficients are subsequently considered as the extracted features, which are then passed through the CNN-based classifier network. Details of this network are further detailed in the following.

2.1 Convolutional Neural Networks

Introduced by [31], CNNs are representational structures that can automatically extract high-dimensional characteristics from the data. This approach combines the jobs of feature extraction and classification into one learning block. This deep learning technique is basically inspired by the structure and operational approach of the human visual cortex. Although CNNs are originally meant to handle 2D and 3D data like images or videos, typically for visual recognition problems, they have been used extensively in a variety of other applications, such as speech recognition [32], natural language processing [33], classification of electrocardiogram (ECG) beats, fault detection in power engines [34], detecting structural damages [35, 36, 37] etc.

Convolutional, sub-sampling, and fully linked layers—also referred to as classification layers—commonly constitute a typical CNN network. Each input signal is convoluted with a set of
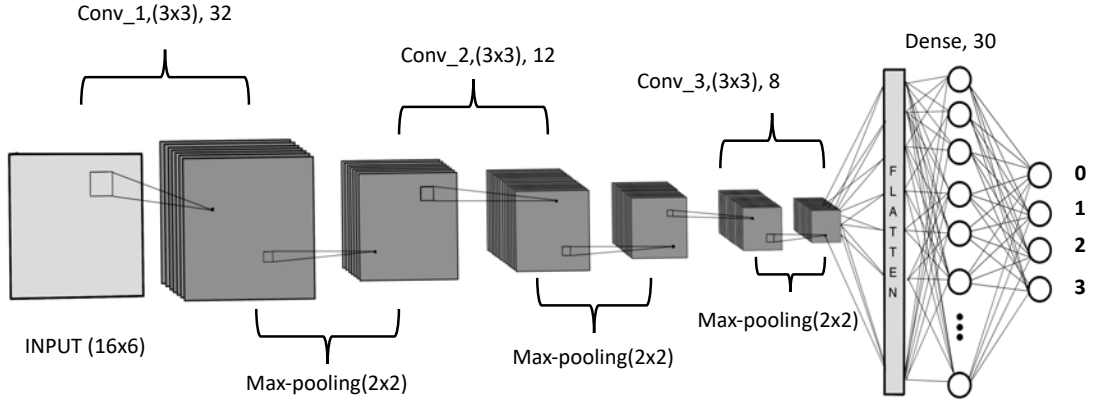
Figure 1: Schematic diagram of the proposed 2D-CNN network

filters or kernels in the convolutional layer in order to fetch the location of the data resembling the filters. The subsequent sub-sampling layer produces a highlighted data array as a feature map through the pooling operation. In order to obtain more intense feature maps, several such convolution and sub-sampling layers are stacked. This yields a compressed feature map, where the fully-linked classifier associates each of the input sequence layers to the corresponding label. Typically, ReLU is employed as an activation function to retrieve these features. The network is schematically given in Figure 1.

3 Building database

The semi-submersible floating system is shown in Figure 2, designed as part of the Deep-Cwind project (cf. [20]). The same is simulated for this study using NREL's open-source wind turbine simulation tool OpenFAST. In the absence of real data, the model hereby is considered here as the "real" structure from which the training and validation datasets are simulated. Single point response time history corresponding to all 6 *dof*s (transverse and rotations) are considered as the input. The simulation is undertaken under several metocean and structural conditions while taking into account a straightforward mooring system by rebuilding the modules as specified in [20].

In this study, four main damage types—biofouling, corrosion damage, and bottom segment (anchorage) failure—have been discovered as being relatively common in the context of failure modes in the mooring lines. The accumulation of seaweed, bacteria, plants, algae, and animals along the mooring line causes bio-foiling, which makes the line heavier and increases its dampening capabilities. Due to harsh salty water and aerobic microbe on the surface of the mooring line, mooring reduces its elasticity due to pitting corrosion. Further, the static friction in the anchor may be, at times, insufficient to hold the bottom connection in place and to prevent the entire FOWT from moving to its next equilibrium point. This aspect may cause the bottom section failure or anchorage failure.

By describing modifications to the module, OpenFAST recreates these failure modes. The default value of MoorDyn's mass per unit length is 113.35 kg/m; a 10% mass (approximately approx 124.69 kg/m) is increased in this case to replicate major bio-fouling. Due to pitting corrosion, which normally impacts stiffness, the elasticity of the mooring line is reduced by 10%.e (from 7.536e8 to 6.783e8 N/m^2). Similar to this, the bottom node for the mooring is shifted by ± 20m in the model from its original position to simulate anchorage failure.

In the following, the model is simulated under several metocean conditions through the varying wave and wind loading in the healthy as well as the damaged condition of the FOWT. A total of 1200 scenarios are simulated in this attempt with 300 sample cases for each four health states (300×4). A single point response measurement for all six *dof*s are sampled for a constant sampling frequency of 40 Hz for $1000secs$ and subsequently, the stabilized response is employed for training and validation.
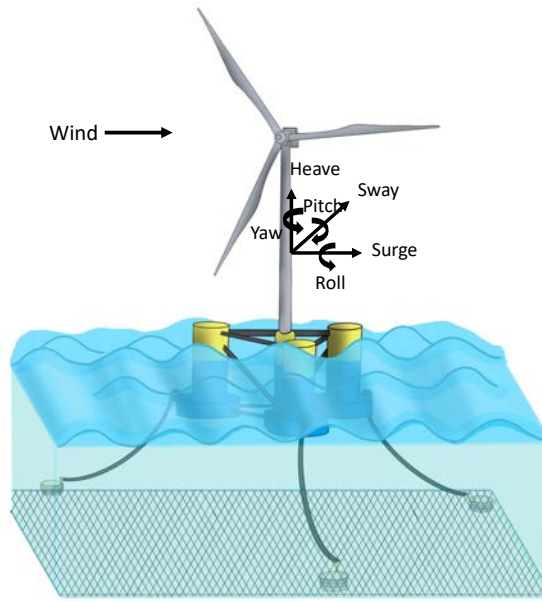
Figure 2: Schematic representation of a semi-submersible FOWT

Figure 3 shows the overview of the proposed approach.

The database for training and validation is subsequently been modelled with AR modelling approach with a suitable model order chosen followed by the method detailed earlier in this manuscript. The AR model coefficients corresponding to each sample database are further associated to a damage case (as labels) already detailed. Next, these extracted ARMCs are trained against their corresponding labels employing a 2D CNN network.

For choosing model order, the AIC for all model orders ranging from 1 to 30 are calculated for response samples for all six *dof*s and the average value is plotted in Figure 4. The AIC is observed to be stabilizing over increasing model order. Since with increasing model order, the computation increases exponentially, a practical value for the model order is typically identified from this graph using the elbow method. In this approach, the elbow could be found around the model order 16 and accordingly, 16 is selected for the optimal model order. Next, the adopted model order is checked for its prediction accuracy through the Q-Q plot, wherein the whiteness and stationarity of the residual are ascertained (cf. Figure 5). For the sake of brevity,
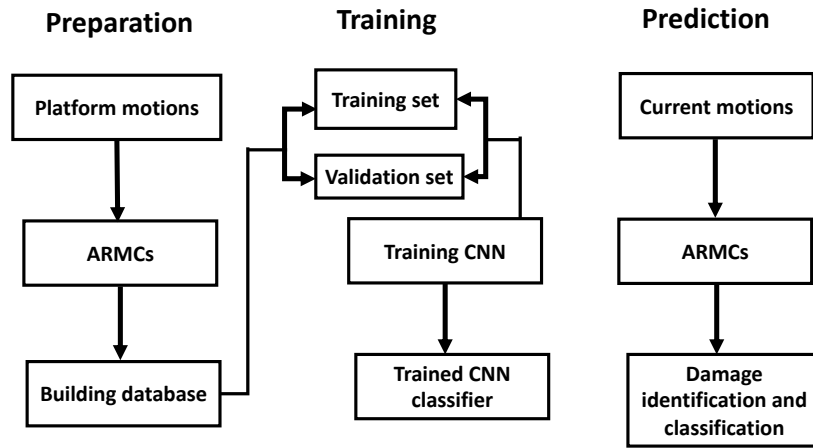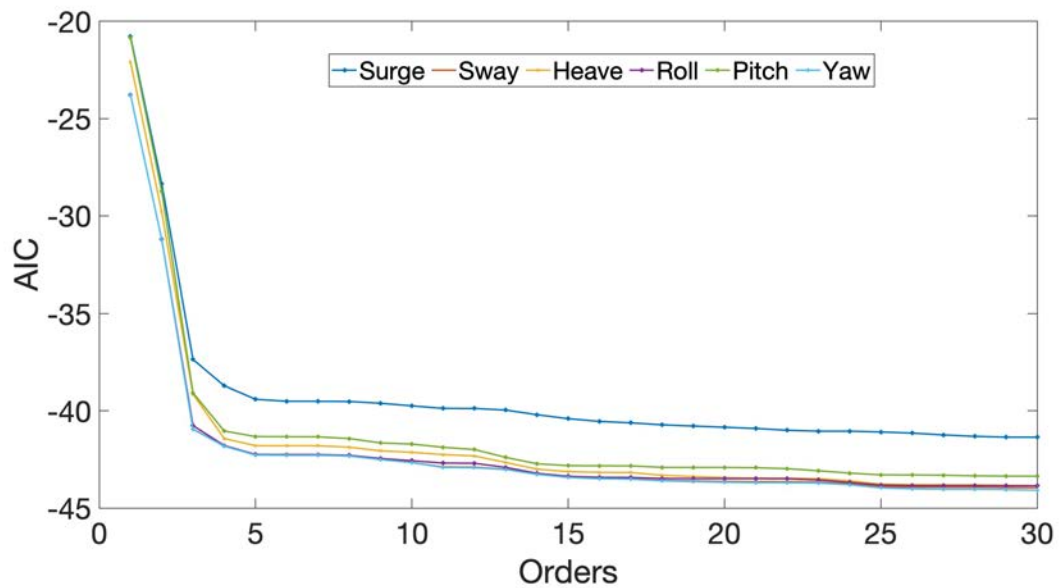
Figure 3: Flowchart of the proposed method

Figure 4: AIC of different orders of AR Model considering all motions
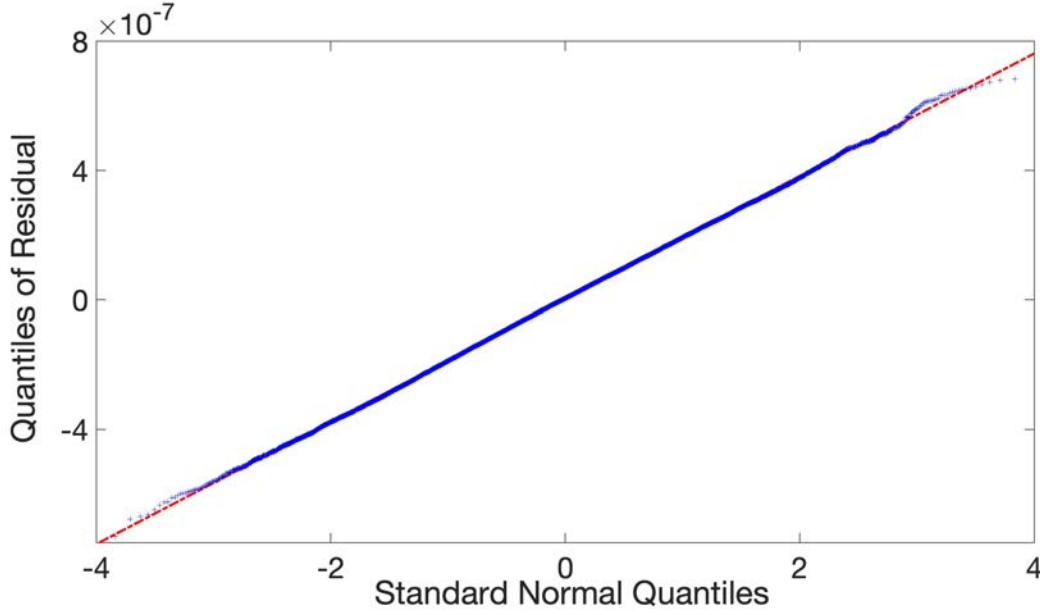
Figure 5: Normality Test of Residuals (Q-Q Diagram) considering only a surge motion

the figure, however, presents the results corresponding to only surge motion as a representation of all motions that also demonstrate similar behaviour.

Eventually, all other sample databases are modelled with the AR approach using adopted model order of 16, yielding 6×16 coefficient matrices that are further needed to be classified against their damage labels using CNN as gray-scale images of resolution 6×16.

4   Network design and training

The following two viewpoints determine how the training and test set are divided. Firstly, to provide better training outcomes, the amount of samples in each category in the training set should be as evenly as possible distributed. Secondly, in order to facilitate comparative analysis, the test set should include samples with various operating scenarios (i.e. different metocean and health conditions). Out of 1200 samples, 10% of the data from the training set were randomly chosen to make up the validation set. As a result, 10% samples from each case in the database are picked to form the test set. Each input is basically a 16×6 pixel resolution matrix (cf. Figure 1) which is then sequentially reduced in dimension through three stacks of convolution and pooling layers before being classified via a single fully-connected layer. The filters are assumed to be of the equal dimension of 3×3 for all convolution layers. The architecture is further detailed in the following.

$$
\begin{aligned}
&\text{Conv2D(ReLU, 3x3, 32)} \rightarrow \text{Maxpooling } (2 \times 2) \\
&\text{Conv2D(ReLU, 3x3, 12)} \rightarrow \text{Maxpooling } (2 \times 2) \\
&\text{Conv2D(ReLU, 3x3, 8)} \rightarrow \text{Maxpooling } (2 \times 2) \\
&\text{Dense (ReLU, 36)} \rightarrow \text{Dropout(0.2)} \\
&\text{Dense (Softmax, 4)}
\end{aligned}
\tag{8}
$$

In the proposed network, the probability of the four damage cases across the two fully connected layers is determined using the Softmax function and Cross entropy loss (cf. equation 9) as cost function. The dropout is discovered in the second fully-connected layer and all convolutional layers, as well as the first fully-connected layer, have the ReLU set. A learning rate of

1×10^{-3} and a batch size of 32 is used. The stochastic gradient descent (SGD) optimization scheme is used in the training process. The network is trained by placing constraints over the number of epochs(600), threshold loss and the difference between training and validation loss.

$$L_{CE} = -\frac{1}{n} \sum_{n=1}^{n} y \log \hat{y} + (1 - y) \log(1 - \hat{y}) \tag{9}$$
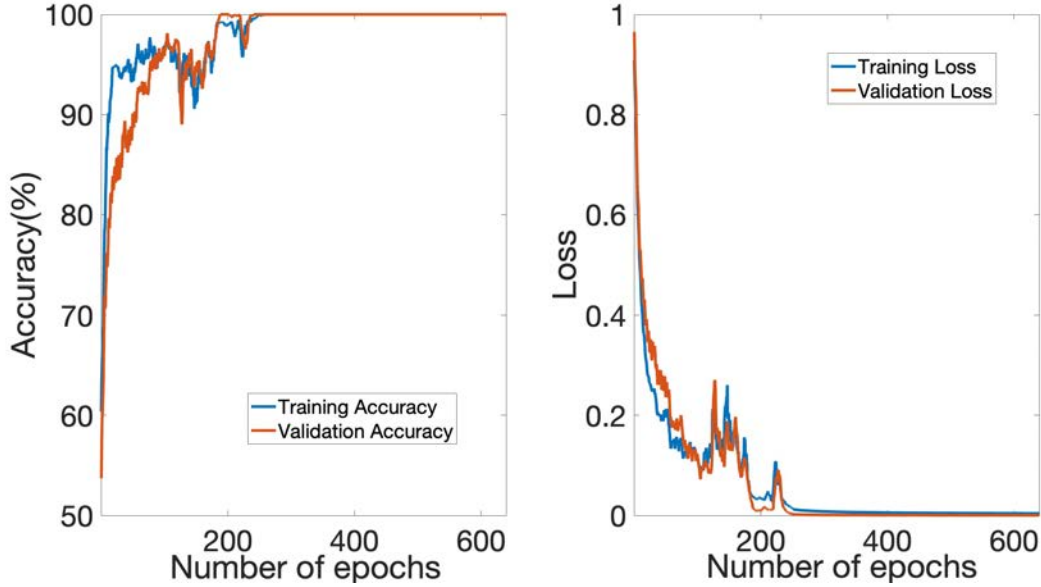
5 Results and Conclusion

Figure 6: Accuracy and loss curve for the proposed 2D CNN network

Two aspects are typically considered necessary to quantify the efficiency of a ML network: accuracy and loss percentage. Accuracy is the percentage of samples that the model correctly classifies. The mean of the loss function for each training epoch for the mini-batch is referred to as average loss. The loss and accuracy curve for the proposed approach is shown in Fig 6.

The results show that as the accuracy increases, the average loss attenuates gradually. Also, it can be observed that the accuracy of training and validation is similar, reaching their final values quite similarly. Eventually, the results demonstrate that the proposed strategy of combining ARMC with CNN and the adopted CNN architecture can extract the high-dimensional damage-sensitive properties of ARMCs and has better generalization capabilities. The confusion matrix plots are additionally shown in Figure 7.

The construction of DSFs using the conventional AR model-based damage diagnosis methods is arbitrary, time-consuming, and labor-intensive. Therefore, the CNN's are used to swiftly and automatically extract the features from ARMCs in light of these drawbacks. Consequently, an AR model and CNN-based structural damage detection and classification method are suggested. The proposed network further takes benefit of the spatio-temporal information embedded within the response array recorded simultaneously from several sensors, which introduces the correlation information between different responses for damage detection purposes.

When predicting mild damage failure modes in turbine mooring lines, the constructed network achieves 100% accuracy. As anticipated, the proposed technique has greater robustness

Figure 7: Confusion matrix of the proposed AR with CNN method

and efficiency. As only the motions of the platform would be required to remotely estimate the future of a mooring system's health status, this technique could drastically reduce O&M costs, increasing the overall profitability. Later in this research, the technique will further be expanded to any FOWT while taking different structural components into consideration in order to identify and categorize structural damage for more complex circumstances. The several failure modes that may occur simultaneously must also be considered when defining the damage type using CNN-based techniques.

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