**Proceedings of the ASME 2022 41st International Conference on Ocean, Offshore and Arctic Engineering OMAE2022 June 5-10, 2022, Hamburg, Germany**

# OMAE2022-78603

# REVISED DRAFT: ASSESSMENT OF SEA STATE ESTIMATION WITH CONVOLUTIONAL NEURAL NETWORKS BASED ON THE MOTION OF A MOORED FPSO SUBJECTED TO HIGH-FREQUENCY WAVE EXCITATION

**Gustavo A. Bisinotto**
Universidade de São Paulo
Numerical Offshore Tank (TPN)
São Paulo – SP, Brazil

**Lucas P. Cotrim**
Universidade de São Paulo
Numerical Offshore Tank (TPN)
São Paulo – SP, Brazil

**Fabio G. Cozman**
Universidade de São Paulo
São Paulo – SP, Brazil

**Eduardo A. Tannuri**
Universidade de São Paulo
Numerical Offshore Tank (TPN)
São Paulo – SP, Brazil

## ABSTRACT

*Motion-based wave inference has been extensively discussed over the past years to estimate sea state parameters from the measured motions of a vessel. Most of those methods rely on the linearity assumption between waves and ship response and present a limitation related to high-frequency waves, whose first-order excitation is mostly filtered by the vessel.*

*In a previous study in this project, the motion of a spread-moored FPSO platform, associated with a dataset of environmental conditions, was used to train convolutional neural networks models so as to estimate sea state parameters, displaying good results, even for high-frequency waves. This paper further explores this supervised learning inference method, focusing on the estimation of unimodal high-frequency waves along with an evaluation of particular features related to the approach.*

*The analysis is performed by training estimation models under different circumstances. First, models are obtained from the simulated platform response out of a dataset with synthetic sea state parameters, that are uniformly distributed. Then, a second dataset of metocean conditions, with unimodal waves observed at a Brazilian Offshore Basin, is considered to verify the behavior of the models with data that have different distributions of wave parameters. Next, the input time series are filtered to separate first-order response and slow drift motion, allowing the derivation of distinct models and the determination of the contribution of each motion component to the estimation. Finally, a comparison among the outcomes of the approach based on neural networks evaluated under those conditions and the results obtained by the traditional Bayesian modeling is carried out, to assess the performance presented by the proposed models and their applicability to face one of the classical issues on motion-based wave inference.*

Keywords: Sea state estimation; convolutional neural networks; moored FPSO; high-frequency waves.

## 1. INTRODUCTION

Accurate information about the wave spectrum and associated sea state parameters can be traditionally obtained by moored wave-buoy measurements. Those devices are equipped with sensors to record their motions, allowing to recover the environmental conditions that induced them. However, that setup is subjected to damage and loss, and suffers from deep water mooring drawbacks.

During the past years, these measurements systems have been complemented by monitoring data from different devices, such as wave radars, and results from wave estimation systems with the application of motion-based inference, using the wave-buoy analogy, in which the vessel itself is considered as a wave-buoy.

When compared to traditional measuring, motion-based methods present the main advantage of the simplicity of the instrumentation (composed basically of accelerometers and rate-gyros), which is very easy to install on-board and requires a rather simple maintenance. On the other hand, the limitation is also clear: only waves that impose a reasonable level of motion can be inferred, which means that the vessel acts as a low-pass filter, filtering the high-frequency components that do not excite the vessel's first-order response [1].

This filtering behavior is illustrated in Figure 1. For low-frequency incident waves (on bottom), oscillatory motions are generated in the wave frequency (first-order response). While it can be noticed that for high-frequency waves (on top) the vessel is mostly not responsive to the wave excitation, and hence little first-order motion is induced.

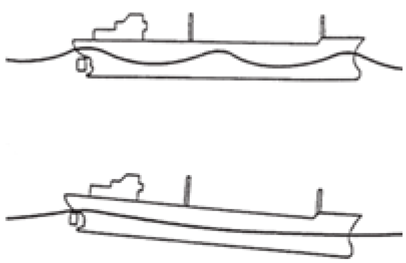

**FIGURE 1**: Illustration of the filtering problem

Besides the first-order responses, two additional components of motion induced by waves can be observed: the mean drift motions, that result from constant loads associated with the inversion of momentum during the wave reflection on the vessel surface, and the slow drift motions, which are caused by non-linear hydrodynamic forces due to the iteration between wave components with different frequencies in an irregular sea, that can excite the system in the range of the natural frequencies of the vessel.

This study aims to further explore the results described in a previous publication within this same research project (see Ref. [2]), in which time series of motion of a moored FPSO (Floating Production Storage and Offloading) unit were considered to estimate sea state parameters associated to unimodal waves with convolutional neural networks models, providing a good performance, even in the high-frequency range. In this paper, a similar inference procedure is carried out, with focus on the analysis of the estimation of parameters associated with high-frequency waves, that is a known limitation of motion-based approaches.

Some alternatives were already discussed in the literature to deal with that particular estimation problem, most of them seeking to provide additional information so as to assist the inference. A parametric estimation method was evaluated, in Ref. [3], with two sets of motion: one with the three vertical motions {heave, roll and pitch} and the other with the replacement of pitch by the relative motion {heave, roll, relative motion}. It was verified that, in the general case, the results with both sets were similar, but better estimations were obtained with the basis {heave, roll, relative motion} for high-frequency wave excitation.

An extended formulation of the Bayesian modeling was proposed in Ref. [4] to incorporate measurements from wave-probes as additional degrees of freedom (dofs). Different arrangements of probes were considered and compared, showing that the inclusion of the probes was able to improve not only the estimation of energy coming from high frequencies, but also in the entire frequency range of the spectrum.

Regarding studies with neural networks, in Ref. [5] an estimation procedure based on the power spectra of the vertical motions was investigated, with the addition of the responses of vertical bending stress to provide a better high-frequency behavior.

This paper is organized as follows: the next section presents a general description of fully connected and convolutional neural networks. After that, the platform considered in this study is characterized, along with the process to generate the time series of motion from different datasets of environmental conditions (Section 3). In Section 4, the estimation procedure is defined with an initial step of data treatment, followed by the description of the proposed neural network architecture and the formulation of the Bayesian method for comparison of estimations. Section 5 presents the wave estimation results obtained from the different datasets of platform motions, and comparisons among them. Finally, Section 6 draws the main conclusions of the study.

## 2. NEURAL NETWORKS

Artificial Neural Networks (ANN or simply NN) are data-driven models that essentially aim to approximate some function $\boldsymbol{y} = f^*(\boldsymbol{x})$, which maps an input $\boldsymbol{x}$ to a continuous value or a categorical output $\boldsymbol{y}$, defining a relation $\boldsymbol{y} = f(\boldsymbol{x}; \boldsymbol{\vartheta})$, and to learn the value of the parameters $\boldsymbol{\vartheta}$ that results in the best function approximation [6].

A fully connected neural network, also called multilayer perceptron (MLP), consists of a number of layers, each with a number of neurons, each taking a linear combination of the outputs of the previous layer and weights as input to an activation function to generate the output of the node. The mathematical description of the computations performed in a layer $l$ of the network can be expressed as:

$$\boldsymbol{x}^{(l)} = g^{(l)}\left(\boldsymbol{W}^{(l)}\boldsymbol{x}^{(l-1)} + \boldsymbol{b}^{(l)}\right), \tag{1}$$

where $\boldsymbol{x}^{(l-1)} \in \mathbb{R}^{m_{l-1}}$ is the output of the layer $l-1$, which is given as input to the layer $l$, and $m_{l-1}$ is the total number of units in layer $l-1$. $g^{(l)}$ is an activation function that is applied element-wise. $\boldsymbol{W}^{(l)} \in \mathbb{R}^{m_l \times m_{l-1}}$ and $\boldsymbol{b}^{(l)} \in \mathbb{R}^{m_l}$ are, respectively, the matrix of synaptic weights and the bias vector in layer $l$, to be adjusted during the training procedure.

The learning process is carried out by iteratively updating the weights and biases to minimize an error function between the network output and the correct value. As each node in a layer is connected to each node in the next layer, the change that is needed in a node is determined by the combined desire for change coming from all nodes in the previous layer [7]. A typical method used for the purpose of tunning those parameters is the backpropagation, which is described in detail in Ref. [6].

Variations of that basic MLP can provide desirable attributes on pattern recognition of different data structures, such as convolutional neural networks.

### 2.1. Convolutional Neural Networks

Convolutional neural networks (CNNs) form a particular class of neural networks specialized in processing data that have a known, grid-like topology. Those networks use multiple sets of shared weights, called filters or kernels, to respond to different patterns in the data. CNNs encode the input by gradually reducing the dimensions of the data, which can be achieved by the result of applying filters with sizes larger than one, without zero-padding. Besides that, the dimensions of the data can be reduced by pooling – taking only a summary statistic from a number of neighboring elements [7].

In a convolutional layer, the matrix multiplication between input and weights in the formulation of the neurons is replaced by a convolution operation, which can be written for a one-dimensional input ($\boldsymbol{x} \in \mathbb{R}^d$) and a one-dimensional filter ($\boldsymbol{k}$) as:

$$z(i) = (\boldsymbol{x} * \boldsymbol{k}) = \sum_{m=1}^{M} \boldsymbol{x}(i+m)\boldsymbol{k}(m), \tag{2}$$

where $k \in \mathbb{R}^K$ with a kernel dimension $K$, and $K < d$. $z \in \mathbb{R}^q$, with $q = \frac{d-2p-K}{s+1}$, in which $p$ refers to padding and $s$ to the value of the filter stride.

The basic structure of a CNN can be found in Ref. [8], being composed by a series of convolutional layers, with different depths, kernel dimensions and activation functions, and also pooling layers. In this process, it is possible to extract both local features and global combinations of these features from the inputs by combining patterns underlined by each set of filters, which can then be concatenated to feed an MLP for the final step of classification or regression.

## 3. TIME SERIES OF MOTION

Time series were obtained from simulations of the model in 6 dofs of a typical spread-moored FPSO unit, whose characteristics are depicted in Table 1, with one loading condition (single draft – $T = 14m$), under two different datasets of environmental conditions.

The first dataset of metocean information was observed from 2003 to 2009 at a Brazilian Offshore Basin and consists of 18006 different groups of environmental conditions with both unimodal and bimodal seas, defined by a total of up to 10 parameters by example: wind velocity and direction, current velocity and direction and up to 2 sets of wave related parameters – significant wave height ($H_s$), peak period ($T_p$) and mean wave direction ($\beta$). As previously stated, in this paper only unimodal seas were considered, which represented a total of over 5000 observations. The distribution of the wave parameters associated to those seas is shown in Figure 2, with angular values presented in the North-East-Down (NED) reference frame.

**TABLE 1**: Characteristics of the FPSO unit

| Quantity | Value |
|---|---|
| Vessel Type | FPSO |
| Mooring | Spread-Moored |
| Length | 337 m |
| Breadth | 54.5 m |
| Draft | 14 m |
| Heading | 208.94° |

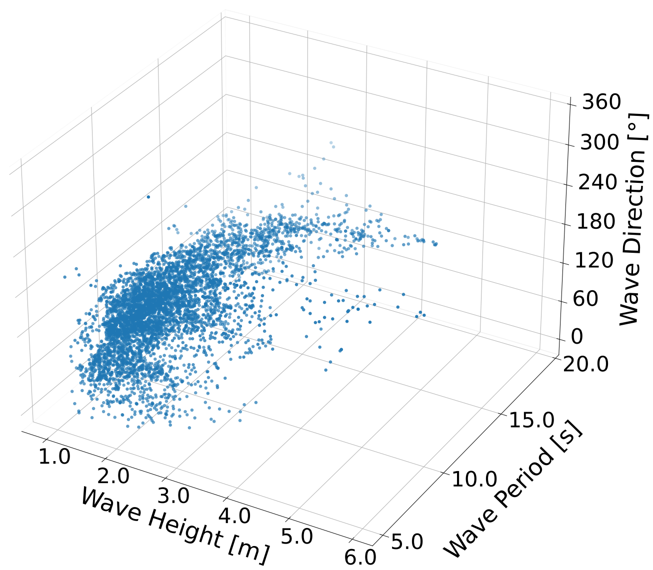


**FIGURE 2**: Distribution of $H_s$, $T_p$ and $\beta$ in the dataset observed at a Brazil's Offshore Basin

The second dataset was built considering only unimodal seas, with synthetic values of sea state parameters, consisting of over 7000 examples. Those parameters were selected in order to be uniformly distributed, as shown in Figure 3, within the same minimum and maximum values of the data observed at the Offshore Basin. In this dataset, no current was considered, but wind parameters were included based on a relation between unimodal waves and wind estimated from the first dataset.

It can be seen in these figures that the data observed at the Offshore Basin is much more concentrated in a region of the space of wave parameters. In particular, most of the wave heights are in the interval between 1 and 3 m, wave periods larger than 15 s are not very common and few cases of wave direction over 200° are observed. The behavior of the direction can be explained by the geographical position of the platform (in the southeast Brazilian coast), in such a way that those waves with few oc-

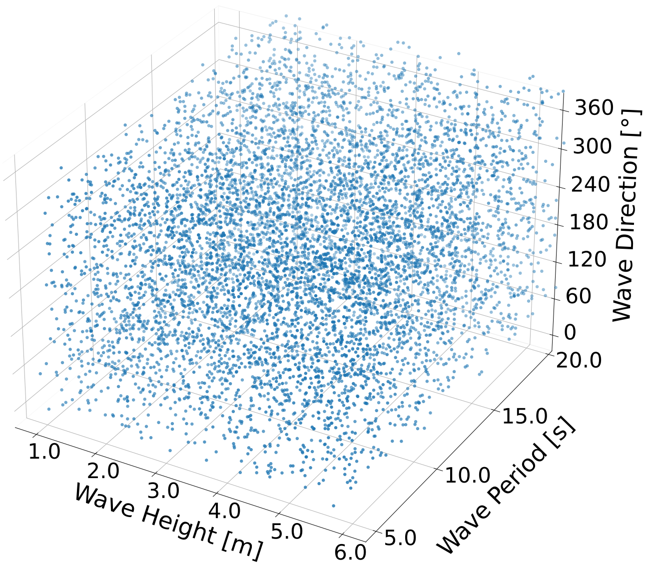


**FIGURE 3**: Distribution of $H_s$, $T_p$ and $\beta$ in the dataset built with uniformly distributed sea state parameters

currences would be coming from shore, which is naturally less frequent. For the uniform data, it can be noticed that a cloud of data points fills the entire space, as expected by the construction of the dataset.

For data generation, the simulation model, along with the platform information and the environmental conditions were inserted as inputs in the Dynasim simulator, a hydro-dynamical numerical simulator developed by a partnership between the Numerical Offshore Tank Laboratory of the University of São Paulo (TPN-USP) and Brazilian Petroleum company (Petrobras), which allows the study of the dynamic behavior of the moored platform.

The output of the simulator, for each set of conditions, is composed by 18 time series (position, velocity and acceleration in the 6 dofs: surge, sway, heave, roll, pitch, yaw) with a sample time of 1 s and length of simulation of over 3 hours (11400 s).

## 4. ESTIMATION PROCEDURE

The proposed estimation procedure was formulated as a supervised learning regression problem, where the goal is to compute each one of the sea state parameters (significant height, peak period and incidence direction) of a unimodal sea from time series of motion of a moored platform.

To evaluate the influence of each wave induced motion in the inference process, the time series were filtered to separate the first-order response and the slow drift motion (the mean drift motion was not considered), which allowed the definition of models from the unfiltered data – similarly to what was done in Ref. [2] – and also two other groups of models trained exclusively from the two filtered components of the time series.

Besides that, for comparison purposes, the data from the time series with the first-order response were taken into account so as to obtain estimations from the well-established Bayesian method for wave inference.

### 4.1. Data Treatment

Before deriving the estimation models, a data treatment procedure was carried out on the data generated by the Dynasim simulator.

From the complete set of time series, just the data of the 6 positional motions were selected in a time window of 30 min, with the same sample time of 1 s, resulting in time series with 1800 points. The initial instant of each set of time series was randomly chosen within the total duration of the simulation, in order to prevent the estimation model from creating a dependency with a specific time span, and to allow a better generalization to any realization of equivalent waves.

A change of coordinates was performed in the linear horizontal motions (surge and sway), which were exported in the global reference frame, to express them with respect to the local reference. Next, each time series was centered by subtracting its mean value, removing the influence of the mean drift motion.

After that, the time series were filtered with an exact low-pass filter, whose frequency response is shown in Figure 4. The filter was designed so as to pass the entire signal when the frequency is lower than the cutoff – which was defined as 0.025 Hz (or 40 s) – and completely attenuate the signal in higher frequencies. In this way, the slow drift motion could be separate from the original data, and the first-order could be obtained by subtracting the slow drift motion from the unfiltered series. Examples of the first-order response and the slow drift motion, compared to the unfiltered time series, are presented on Figures 5 and 6, respectively.

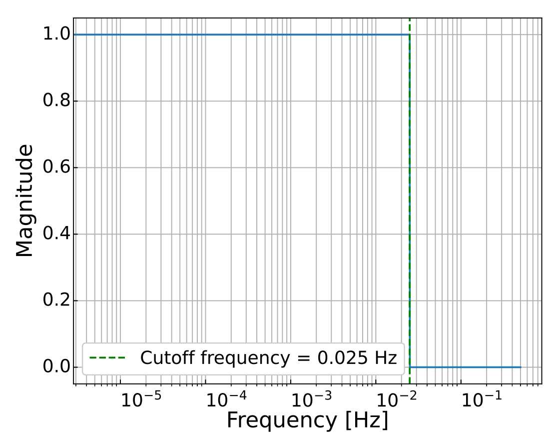


**FIGURE 4**: Filter frequency response

Therefore, three datasets of platform motions (for each dataset of environmental) conditions could be built: unfiltered data, first-order response, and slow drift motion. Each of those sets was then divided into 3 different datasets, following a 70/20/10 split: the training data, to be used in the training of the network, the validation data, used for the evaluation of the

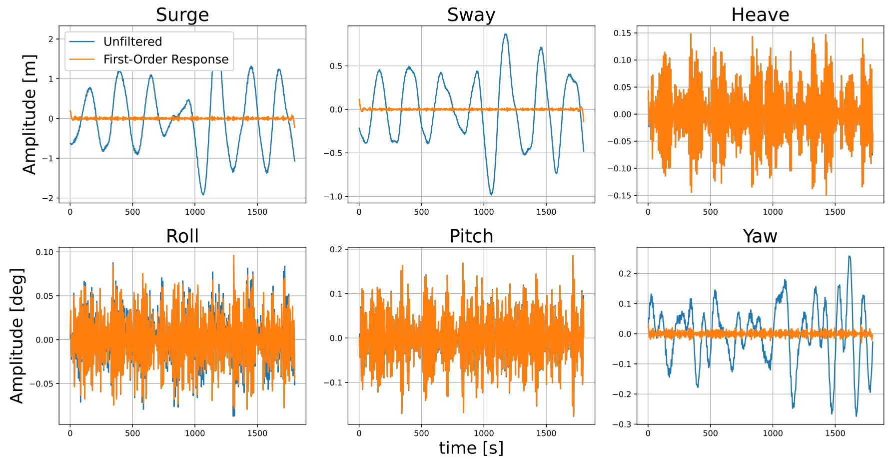


**FIGURE 5**: First-order response

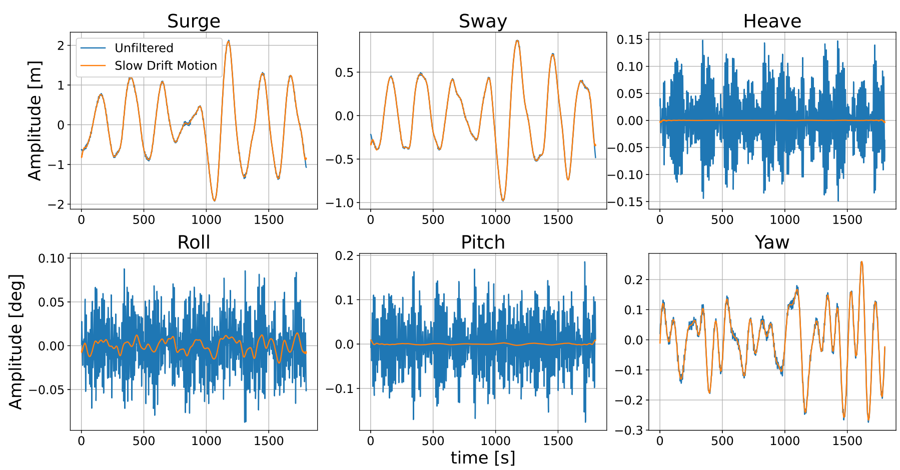


**FIGURE 6**: Slow drift motion

model with the desired metrics and the test data, to verify the performance of the system on previously unseen data.

For the derivation of the neural network models, each dataset was normalized using the statistical properties (mean value and standard deviation) of the respective training data. Besides that, the input 30 min long time series of motion were divided into smaller series that were concatenated to feed the networks. This process followed a sliding window method with a window width of 18 min and an interval of 1 min between two consecutive windows.

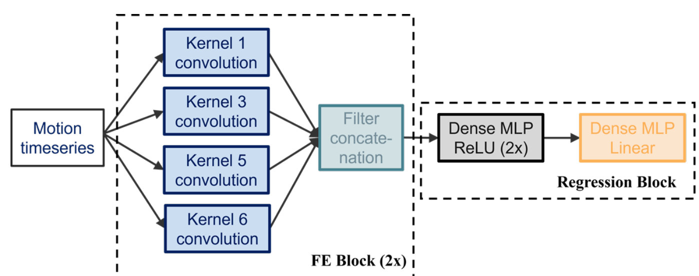


**FIGURE 7**: Network architecture

## 4.2. Network Architecture

The network architecture adopted in this study was largely inspired by the one developed in [2], and it is depicted in Figure 7. The proposed network is composed by 2 Feature Extracting Blocks (FE blocks) which are based on one-dimensional convolutional layers (CNN1D) and a Regression Block with MLP layers.

Each feature extracting block consists of four basic CNN1D with the same number of filters (256 in the first FE Block and 128 in the second), but multiple kernel dimensions, such that features related to the coupling of different combinations of motions can be extracted with different kernels.

For each filter, the operation performed in a convolutional layer can be expressed as:

$$\boldsymbol{Z} = ReLU\left(BN\left(\boldsymbol{X} * \boldsymbol{K} + \boldsymbol{b}\right)\right), \tag{3}$$

where $\boldsymbol{Z}$ is the feature map (output) of the layer, $\boldsymbol{K}$ is the filter, $\boldsymbol{b}$ is the bias and $\boldsymbol{X}$ represents the input. For the convolution operation, a unitary filter stride and no zero-padding were considered. In this way, the features extracted by the linear convolution will be processed by a batch normalization layer (BN) and then passed through the rectified linear unit (ReLU) activation function. After that, the feature maps of all four CNN1D are concatenated to generate the input for the next block.

In the regression block, the final steps of the estimation are performed, with two MLP layers (128 and 64 units, respectively) associated to a ReLU activation function, followed by a linear output layer.

The experiments were carried out within a computational environment with Python 3.8.5. The layers were implemented by Keras 2.5.0, using TensorFlow 2.5.0 as the backend. The training process used the Adam optimizer, a batch size of 32 and a number of epochs of 1000. The selected loss function was the mean absolute error (MAE) between the actual and the estimated value of the sea state parameter. The best model (based on the validation set) was stored during training.

### 4.3. Bayesian Modeling

The motion-based wave inference method based on Bayesian modeling was also implemented for comparison basis. The approach was originally proposed by Iseki and Ohtsu [9] and essentially aims to minimize the errors between the estimated and the true motion spectra, which can be modeled as a Gaussian white noise. This procedure leads to an ill-conditioned inverse problem, hence a-priori information about the wave spectrum can be included in the formulation to improve the estimation.

Ultimately, the inference method requires the minimization of the following functional, leading to a quadratic optimization problem:

$$J(\boldsymbol{x_s}) = ||\boldsymbol{B} - \boldsymbol{A}\boldsymbol{x_s}||^2 + \boldsymbol{x_s}^T \left(u_1^2\boldsymbol{H_1} + u_2^2\boldsymbol{H_2} + u_3^2\boldsymbol{H_3}\right)\boldsymbol{x_s}, \quad (4)$$

Where $\boldsymbol{x_s}$ is the vector with the unknown spectrum values for different wave frequencies and directions, from which the wave related parameters can be computed. The vector $\boldsymbol{B}$ denotes the values of the spectra and the cross-spectra of motion, which are derived from the simulated first-order response of the platform, obtained from the time series generated by the Dynasim simulator. $\boldsymbol{A}$ is the matrix that contains the dynamic characteristics of the vessel, expressed by means of its linear transfer functions of motion (RAOs).

The second term in the functional allows one to predefine different levels of smoothness of the estimated spectrum regarding its variation in frequency and direction and also avoids predicting spurious wave energy for frequencies outside the range of wave frequencies for which the vessel presents significant response.

Smoothness is modulated by means of the hyperparameters $u_1$, $u_2$ and $u_3$, which should be properly calibrated as they control the trade-off between good fit to the data and the enforcement of the previously available knowledge about the spectrum. Therefore, their selection was performed based on the considerations presented in [10], in which a methodology for pre-defining those hyperparameters was proposed. Completing the description of the functional, matrices $\boldsymbol{H_1}$, $\boldsymbol{H_2}$ and $\boldsymbol{H_3}$ can be computed from the definition of the vector $\boldsymbol{x_s}$ (see, for example, [11]).

The Bayesian method was implemented with MATLAB® R2020a. The numerical model of the RAOs was obtained in frequency-domain using the software WAMIT [12], which considers linear wave potential theory and panel method.

A set of five input motions was considered for the inference, which comprised all dofs other than roll (due to the uncertainties related to the linear description of the roll motion [1]). Welch's technique was used for the estimation of power and cross-spectra of motions from their time series. Each motion record was divided into eight sections with 50% overlap, each section being filtered by a Hanning window. A moving-average filter, with 21 mean values, was applied in order to smooth the computed motion spectra. The quadratic optimization problem was defined with a number of 36 wave directions, representing a spatial resolution of 10°, and 25 frequencies, with a regular discretization between 0.16 rad and 1.57 rad (periods from 4 s to 40 s).

## 5. RESULTS

For each set of environmental conditions (uniformly distributed and observed at a Brazilian Offshore Basin) and each sea state parameter – significant height, peak period and mean direction, a total of three neural networks estimation models were trained and validated, from the data of each dataset of platform motion: unfiltered data, first-order response, and slow drift motion, following the architecture describe in Section 4.2.

The estimation results obtained from those models, evaluated on the test data, were compared among themselves and also with the wave statistics computed from the directional spectrum estimated with the Bayesian method, which was run considering the same motion data.

All methods were implemented in a desktop computer equipped with a processor Intel i7-11700 with 2.50 GHz and 8 Cores, and Nvidia GeForce RTX 3070. In this setup, the training procedure of the neural networks took up to approximately 2400 s (about 2.4 s/epoch for a maximum of 1000 training epochs). The estimation itself, after the training process, required less than 0.5 s. For the Bayesian approach, nearly 3.8 s on average were necessary for each estimation directly from the time series of motion.

Plots of error metrics were used to illustrate and compare the performance of the models. Percentile errors are presented for significant height and peak period, whereas mean direction errors are displayed in absolute values. Bars indicate the percentile of those errors which are differentiated by a scale of color intensity: the stronger color indicates the 50th percentile, the middle one corresponds to the 90th percentile and the 95th percentile is represented by the most transparent among the stacked bars.

Figures 8, 9 and 10 show the results for the three wave parameters obtained from the motions generated by the dataset of uniformly distributed environmental conditions From the errors plots of significant height, it can be observed that in the lowest periods of the interval (5 – 8 s) the Bayesian method generated the estimations with the larger deviations from the true values, when compared to the approaches based on convolutional neural networks. This behavior is expected as a known limitation of the method in the inference of high-frequency (low period) waves, as already discussed in [4]. For waves in this range of periods, the induced first-order response is influenced by the filtering effect, however, the neural model was able to associate the time series of motion of the platform with the correspondent wave with good accuracy – 22.3% of 95th percentile error and 6.7% in the 50th percentile. For the slow drift motion, despite the nonlinear (quadratic) relation between wave height and vessel response, good comparative results could be attained. In this way, similar values of error were also produced by the model obtained from the unfiltered data.

Moving to the larger periods, a common trend is verified for the Bayesian and first-order response, which is a reduction of the errors as the period increases. That could be anticipated, as the influence of filtering decreases, and for waves with long periods, the vessel tends to simply follow the elevation of the free-surface. The errors also decrease for the unfiltered data, as the contribution of the first-order to the complete motion becomes more relevant. On the other hand, the results obtained out of the slow drift motion remain almost constant during the entire range of periods.

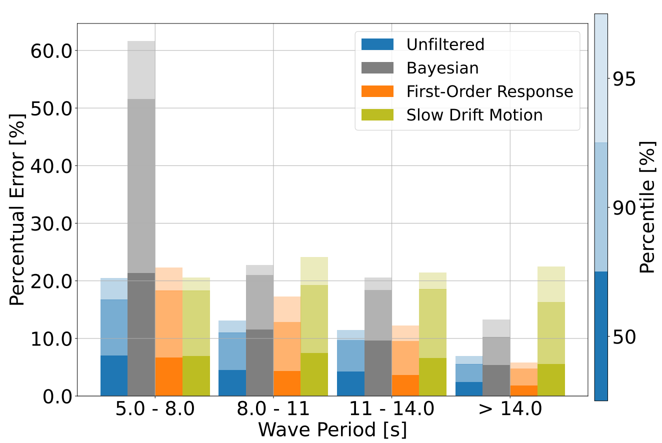


**FIGURE 8**: Percentual error $H_s$ – Uniform environmental data

Analyzing the peak period results, similar observations can be taken for the outcomes from the first-order and unfiltered data – less than 7% of error in 95th percentile and no more than 2% in the 50th percentile in the high-frequency range. The errors from the slow drift motion, despite decreasing as the wave period increases, were much higher than those obtained from the other components of motion. This may be associated to the relation between the wave period and the period of the induced slow drift response, which can be given by more pronounced nonlinearities than when compared to the significant height, provoking a more complex association between this wave statistic and the produced slow drift motion. Besides that, a different behavior can be noticed for the estimations from the Bayesian modeling: the 50th percentile value decreases with the increase of periods, as in the wave height; however, the 90th and 95th percentiles presented large variations on the range between 8 and 14 s of period, which indicates that for some cases in this interval, the inference was more challenging, generating wide deviations.

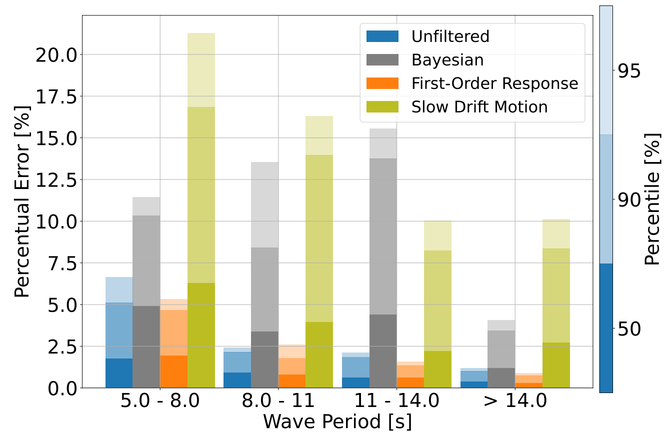


**FIGURE 9**: Percentual error $T_p$ – Uniform environmental data

For the wave direction, it can be clearly observed that the estimation errors from the slow drift data were much larger than all other approaches. This may be due to the fact that the slow drift motion does not carry information about the relative phase between the wave induced motion components, in such a way that the same movement can be produced from port and starboard wave incidences. This seems to influence the results from the unfiltered data on the lower periods, which then follows the behavior of the first-order, that generate low errors for all periods considered – with decreasing errors, starting from 8.8° in 95th percentile and 1.7° in the 50th percentile in the low periods. The performance of the Bayesian method improves as the periods increase, coming close to the values of the neural models in large periods.

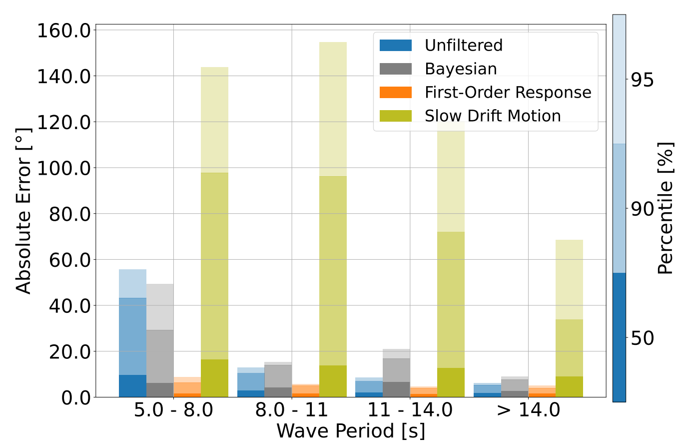


**FIGURE 10**: Absolute error $\beta$ – Uniform environmental data

A further investigation concerns the importance of the roll motion on the estimations. This dof was not considered in the formulation of the Bayesian method, due to the uncertainties related to its linear representation [1], yet it was employed to obtain the results presented with neural networks so far. Hence, in order to assess its influence, experiments were carried out in which neural networks were trained with the first-order response from the uniform environmental data without the roll motion. Those results are displayed in Figures 11, 12 and 13.

From the plots, it can be noticed that, in general, the presence of the roll motion acts in the sense of providing better estimation, especially for height and period statistics, while for the direction, the influence of the presence or absence of movement is not so marked. This can be explained because of the introduction of nonlinearities in the neural network which may allow the relationship between the roll movement and the incident wave to be modeled with greater precision. Moreover, the roll motion provides significant information about the incident wave, given that its natural periods, for FPSO-type vessels, are usually in the range of the wave periods, which may lead to vessel oscillatory motions with large amplitudes.

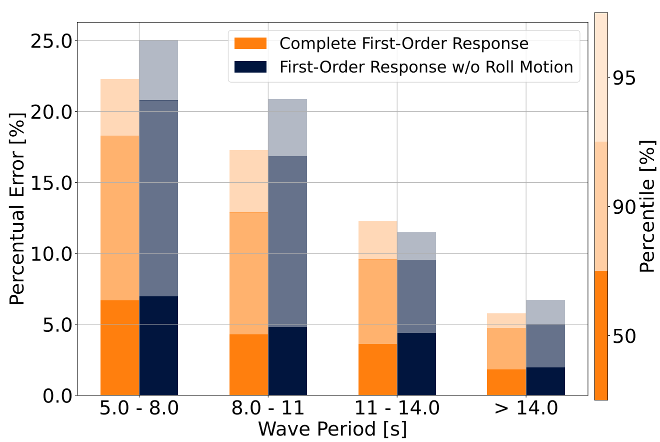


**FIGURE 11**: Percentual error $H_s$ – Influence of roll motion

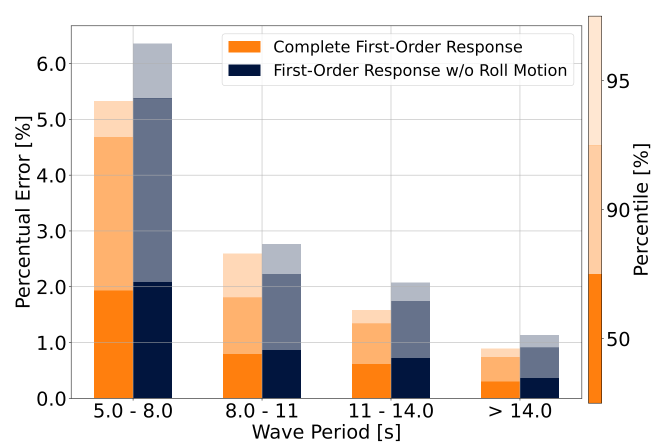


**FIGURE 12**: Percentual error $T_p$ – Influence of roll motion

The results obtained from the metocean conditions observed in the Brazilian Offshore Basin are presented in Figures 14, 15 and 16. In this case, for height estimation, the Bayesian method kept the same tendency of variation as the previous discussion, errors decreasing as the period increases. However, for the results from the neural networks model, some differences can be pointed out: errors on periods between 5 – 8 s and 8 – 11 s are smaller in relation to uniform data, which may be due to the distribution of the observed environmental data, that displays more occurrences in those periods, as shown in Figure 2. Besides that, as the periods grow, the error tends to stabilize or even increase. Those are regions of the space of sea state parameters that were expected to enable a simpler estimation process, as the vessel follows the elevation of the wave, but fewer examples are observed, and, consequently, less data for training the networks, which makes it harder for this data-driven estimation model to obtain accurate results in those intervals of period.

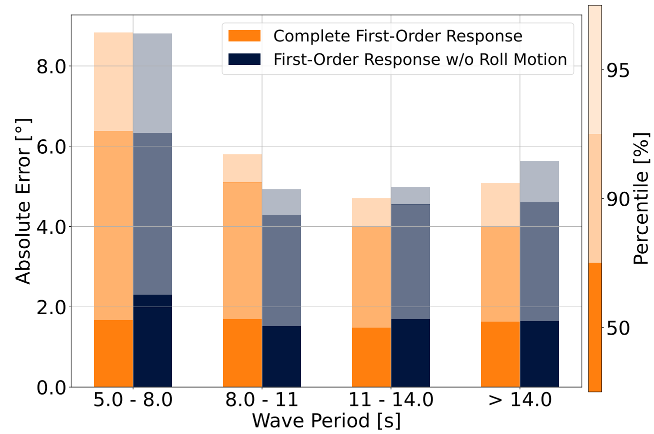


**FIGURE 13**: Absolute error $\beta$ – Influence of roll motion

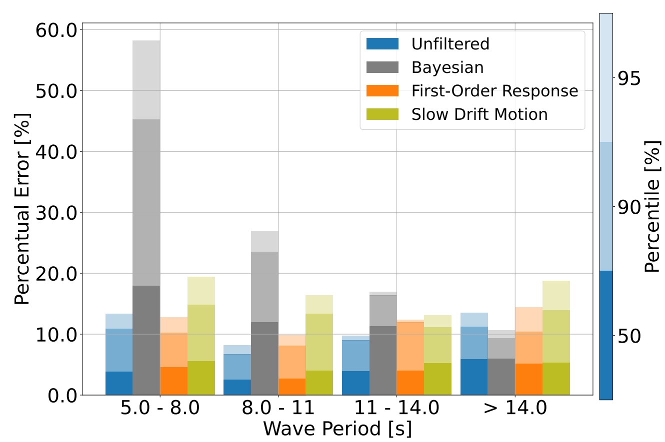


**FIGURE 14**: Percentual error $H_s$ – Offshore Basin environmental data

Regarding the period, the performance of the Bayesian approach is once more similar to the one when considering the uniform environmental data, but the large variation in the 90th and 95th percentiles, with respect to the median, is even more evident. For the neural models, a combination of the previously mentioned behaviors can be verified: the errors are lower than for the uniform data, the influence of data distribution is observable, and also the estimations from the slow drift data are less accurate than those from the other neural models.

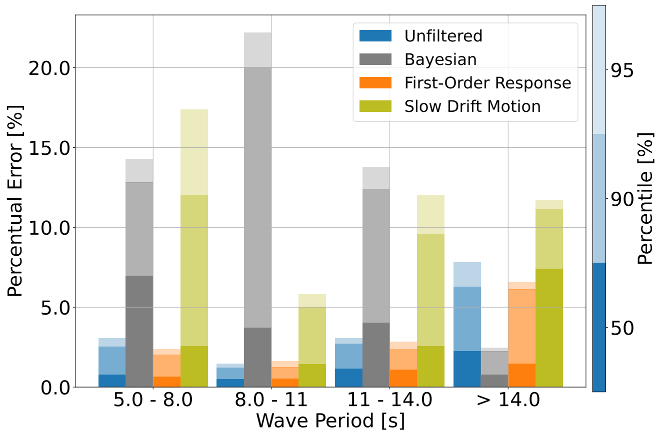


**FIGURE 15**: Percentual error $T_p$ – Offshore Basin environmental data

Finally, on the wave direction, the influence of the distribution of the data given the geographical location is clearly noticed, as the inference errors are much lower with respect to the uniform data, even from the slow drift motion. This may be related to the large angular interval with almost no occurrences of waves (over $100°$), corresponding to conditions that would be coming from the shore. Thus, the algorithm has a more restricted space of desired values, reducing the number of examples with waves that have a symmetric incidence direction with respect to the vessel, leading to better estimations. From the unfiltered and first-order data, good results were obtained in all the considered periods, with absolute values of error slightly smaller than those from the uniform data.

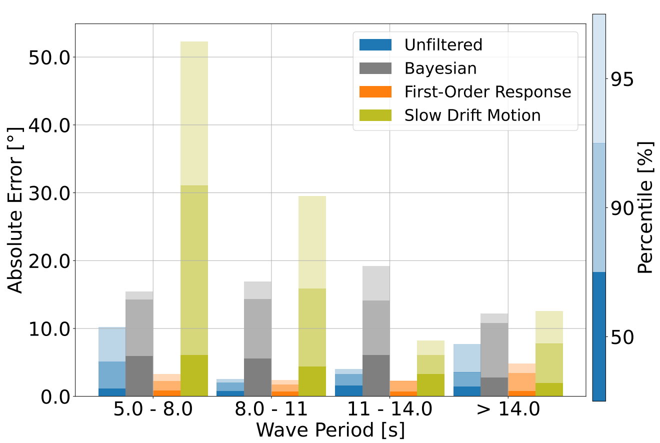


**FIGURE 16**: Absolute error $\beta$ – Offshore Basin environmental data

Therefore, it could be verified that, at least when considering motion data from simulations of the dynamic behavior of the vessel, the use of convolutional neural networks estimation models trained exclusively with the first-order induced motion seems sufficient to carry out sea state estimation, even for low period waves. In some of the evaluated scenarios, the results of neural models derived from the three datasets of platform motions – unfiltered data, first-order response, and slow drift motion – were very similar, such as the significant height, and in others such as the peak period and in particular incidence direction, the presence of slow drift in the movement data appears to negatively influence the estimation process.

## 6. CONCLUSIONS

In this paper, an extended investigation was carried out on top of results obtained in a previous study on the application of convolutional neural networks models so as to estimate sea state parameters from the motions of a moored FPSO using supervised learning. The estimation models were trained from motion time series that were obtained via simulation of the platform out of two datasets of environmental conditions with different distributions of wave parameters. That motion data were filtered in order to build three different datasets: unfiltered data, first-order response and slow drift motion.

A comparative analysis was performed with the results from the estimated sea state parameters for each motion dataset and from the implementation of the traditional Bayesian method. Percentiles of error were presented in different period intervals, in such a way that the evolution of the performance of the estimation models could be evaluated for each period. From that analysis, it was verified that the first-order response was able to provide good estimations for all parameters, even in the low-frequency range when it is influenced by the filtering effect.

Besides that, the importance of the consideration or not of the roll motion in the set of motions for the estimation was examined, and it was observed that for the neural models, the incorporation of this degree of freedom was able to provide better results.

We could also observe the influence of the distribution of the values of the sea state parameters in the datasets for training the models. The obtained results showed that in an unbalanced dataset, the neural models lean towards producing lower estimation errors in the regions of the space of wave related parameters that have more training examples available, even when the association between the vessel motion and the wave parameters of those conditions with few occurrences would be expected to be more straightforward. Moreover, it was noticed that knowledge about the statistical distribution of parameters of a certain location may benefit the inference in some cases, as the network would have access to the additional information, besides the vessel motion data, of the most common conditions at that geographical region.

However, further evaluation is needed to assess these outcomes, as only simulation data were considered to derive the inference models, which despite seeking to precisely represent the dynamics of the vessel, still may disguise practical issues such as sensibility errors of the sensor, possible inconsistent measurements, and noise, that are present in real motion records. The main future development is the validation of our findings with data from real sensor measurements.

## ACKNOWLEDGMENT

Authors acknowledge Petrobras for providing long-term support and motivation to this work. The first author thanks the São Paulo Research Foundation (FAPESP) for the scholarship (process #2021/00409-2). The second author acknowledges the Higher Education Personnel Improvement Coordination (Capes) for the scholarship. The third author was supported in part by Brazilian National Council for Scientific and Technological Development (CNPq) under Grant 312180/2018-7. The last author acknowledges the CNPq for the research grant (310127/2020-3).

## REFERENCES

[1] Simos, A. N., Tannuri, E. A., Sparano, J. V., and Matos, V. L., 2010. "Estimating wave spectra from the motions of moored vessels: Experimental validation". *Applied ocean research,* ***32***(2), pp. 191–208.

[2] Bisinotto, G. A., Cotrim, L. P., Cozman, F. G., and Tannuri, E. A., 2021. "Sea state estimation with neural networks based on the motion of a moored fpso subjected to campos basin metocean conditions". In Brazilian Conference on Intelligent Systems, Springer, pp. 294–308.

[3] Nielsen, U. D., 2008. "The wave buoy analogy—estimating high-frequency wave excitations". *Applied Ocean Research,* ***30***(2), pp. 100–106.

[4] de Souza, F. L., Tannuri, E. A., de Mello, P. C., Franzini, G., Mas-Soler, J., and Simos, A. N., 2018. "Bayesian estimation of directional wave-spectrum using vessel motions and wave-probes: Proposal and preliminary experimental validation". *Journal of Offshore Mechanics and Arctic Engineering,* ***140***(4).

[5] Kawai, T., Kawamura, Y., Okada, T., Mitsuyuki, T., and Chen, X., 2021. "Sea state estimation using monitoring data by convolutional neural network (cnn)". *Journal of Marine Science and Technology,* ***26***(3), pp. 947–962.

[6] Goodfellow, I., Bengio, Y., and Courville, A., 2016. *Deep learning*. MIT press.

[7] Mak, B., and Düz, B., 2019. "Ship as a wave buoy: Estimating relative wave direction from in-service ship motion measurements using machine learning". In International Conference on Offshore Mechanics and Arctic Engineering, Vol. 58882, American Society of Mechanical Engineers, p. V009T13A043.

[8] LeCun, Y., Bengio, Y., et al., 1995. "Convolutional networks for images, speech, and time series". *The handbook of brain theory and neural networks,* ***3361***(10), p. 1995.

[9] Iseki, T., and Ohtsu, K., 2000. "Bayesian estimation of directional wave spectra based on ship motions". *Control Engineering Practice,* ***8***(2), pp. 215–219.

[10] da Silva Bispo, I. B., Simos, A. N., Tannuri, E. A., da Cruz, J. J., et al., 2012. "Motion-based wave estimation by a bayesian inference method: a procedure for pre-defining the hyperparameters". In The Twenty-second International Offshore and Polar Engineering Conference. International Society of Offshore and Polar Engineers.

[11] Nielsen, U. D., 2006. "Estimations of on-site directional wave spectra from measured ship responses". *Marine Structures,* ***19***(1), pp. 33–69.

[12] WAMIT, I., 2020. *Wamit User Manual - Version Hill*. MIT Press.