



Sea Wave Data Reconstruction Using Micro-Seismic Measurements and Machine Learning Methods

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Sea wave monitoring is key in many applications in oceanography such as the validation of weather and wave models. Conventional *in situ* solutions are based on moored buoys whose measurements are often recognized as a standard. However, being exposed to a harsh environment, they are not reliable, need frequent maintenance, and the datasets feature many gaps. To overcome the previous limitations, we propose a system including a buoy, a micro-seismic measuring station, and a machine learning algorithm. The working principle is based on measuring the micro-seismic signals generated by the sea waves. Thus, the machine learning algorithm will be trained to reconstruct the missing buoy data from the micro-seismic data. As the micro-seismic station can be installed indoor, it assures high reliability while the machine learning algorithm provides accurate reconstruction of the missing buoy data. In this work, we present the methods to process the data, develop and train the machine learning algorithm, and assess the reconstruction accuracy. As a case of study, we used experimental data collected in 2014 from the Northern Tyrrhenian Sea demonstrating that the data reconstruction can be done both for significant wave height and wave period. The proposed approach was inspired from Data Science, whose methods were the foundation for the new solutions presented in this work. For example, estimating the period of the sea waves, often not discussed in previous works, was relatively simple with machine learning. In conclusion, the experimental results demonstrated that the new system can overcome the reliability issues of the buoy keeping the same accuracy.

Keywords: sea swell, ocean waves, sea state, sea wave period, buoy, machine learning, micro-seismic data

INTRODUCTION

The complexity of the sea waves is mathematically described by the directional wave spectrum as a combination of waves propagating in different directions with different wavelengths (Talley et al., 2011). The knowledge of the directional wave spectrum is key in several applications such as coastal management and design of coastal and offshore structures (e.g., ports and renewable energy platforms). Indeed, forces on piles, breakwaters, offshore structures as well as wave-induced coastal erosion, all depend on the directional wave spectrum. Recently, accurate wave measurements are required also in marine renewable energy industry for engineering design, and for resource and performance assessments (Thies et al., 2014). Key applications concern verification and data

assimilation into weather and sea waves models to improve their accuracy (Krogstad et al., 2005; Mentaschi et al., 2015).

Fostered by the interest on the numerous applications, technology for ocean observation and monitoring has made significant advances in the last decades (Ardhuin et al., 2019; Lin and Yang, 2020). For example, in the middle of the twentieth century the measurements of the directional wave spectrum were a major achievement, nowadays many systems based on different measuring principles are affordable for operational use. In Krogstad et al. (2005); Souza et al. (2011), good reviews of the available sea state monitoring systems are provided distinguishing two families: remote sensing and *in situ*. Examples of remote sensing systems are those based on radars. These can be ground-based (Wyatt et al., 2003; Lopez and Conley, 2019; Novi et al., 2020), ship-based (Izquierdo et al., 2004), airborne (Voronovich and Zavorotny, 2017; Le Merle et al., 2019; Sun et al., 2020), as well as spaceborne (Macklin and Cordey, 1991; Aouf et al., 2021) and rely on the analysis of the backscattered intensity and/or the Doppler spectrum of radar signals. Examples of *in situ* systems are the subsurface devices, such as pressure and acoustic sensors, but the most common are those based on moored buoys instrumented with motion sensors such as accelerometers, gyroscopes, or GPS as described in Herbers et al. (2012); Andrews and Peach (2019) and in Datawell website.¹ The directional wave spectrum is calculated from the raw measurements by using algorithms based on the hydrodynamics characteristics of the hull.

Buoy technology is well established and recognized as a standard since decades, however, uncertainties have been well demonstrated as discussed in Ashton and Johanning (2015); Ardhuin et al. (2019), Jensen et al. (2021). For example, some issues might arise from the mooring (Nielsen and Simonsen, 2007) or from biofouling (Campos et al., 2021). Furthermore, buoys are installed in a harsh environment, at the mercy of sea waves, wind, storms, and other possible causes of damage. For instance, they might be accidentally damaged by ships when moored next to naval routes, e.g., close to a port. Therefore, buoys are vulnerable to system failures, communication problems, breakage of the mooring, vandalism, etc., and require continuous maintenance. Consequently, data gaps might be very large and frequent, while maintenance costs might be very high. For example, in Picone (2009) the analysis of the data collected from 2002 to 2006 by the 14 buoys of the Italian Data Buoy Network (Piscopia et al., 2003; Bencivenga et al., 2012) revealed that the missing data of the most reliable buoy (Cetraro) were the 15.5% of the total, whereas those of the worst reliable (P. d. Maestra) were the 88.8% (performance of other buoys are shown in **Figure 1**).

The maintenance issues are not specific of the Italian Data Buoy Network, and many works focus on missing data reconstruction using machine learning (ML) and data science methods. For example in Vieira et al. (2020), a method based on artificial neural networks is presented to fill the waves record gaps using offshore hindcast and wind information. In Jörges et al. (2021), a Long Short-Term Memory neural network was used to reconstruct the significant wave height from sea state time

series, weather data of adjacent buoys, and bathymetric data. In Agrawal and Deo (2002), a first order “auto regressive integrated moving average” (ARIMA) model, e.g., see Nielsen (2019), was used and compared to a feed-forward neural-network for making sea wave predictions.

Besides data reconstruction, ML is key in many methods for oceanography (Lou et al., 2021). In fact, ML algorithms can find a mathematical model (called ML model) which produces the desired output when applied to a set of input data (called “training data”). The interesting part is the prediction, in which the ML model generates the correct outputs also when applied to new input data, distinct from the training data, coming from the same source. An important differentiation is between supervised learning and unsupervised learning. In the first case, the desired output is available for the training data, in the latter case, the desired output is not available. Supervised learning is more appropriate for missing data reconstruction because the desired outputs are typically available. For example, the desired output might be the sea wave data measured by a buoy whereas the input data comes from adjacent buoys, wind measurements, offshore hindcast, or, as we do in this work, micro-seismic data. During the regular operation, all data, including the desired output, are available and can be used for training. Instead, when data from the buoy are missing, the ML model will predict them from the input data. There are several ML algorithms able to make both regression (predict a continuous value, such as the significant wave height) and classification (predict a class, such as the degrees of the Douglas Sea scale). For example, there is whole family of algorithms, called artificial neural networks, inspired by natural neural networks. Other algorithms are the results of mathematical approaches, such as linear models, support vector machines, and decision trees. An introduction to machine learning is in Burkov (2019), while a more comprehensive exposition is in Géron (2019).

In this work, we will use micro-seismic data acquired from an onshore seismometer as input data. Actually, it is well known that sea waves are source of a micro-seismic signal which is detectable from onshore, even at many kilometers from the coast. Although this phenomenon has been discovered more than a century ago, the first geophysical model was presented in Longuet-Higgins (1950); more details are provided in the section “Background – From Micro-Seismic Signals to Sea Waves Parameters.” Improvements of this model have been proposed. For example, in Ardhuin et al. (2011, 2012) three different geophysical models were introduced for three different types of events. In other works, the relationship between the micro-seismic signal and the sea waves has been investigated with focus on specific locations (Barruol et al., 2006; Davy et al., 2016; Ferretti et al., 2018) and on specific events (Cutroneo et al., 2021). In Ferretti et al. (2013), an algorithm based on Markov chain Monte Carlo is used to determine the model parameters for a study conducted in the Ligurian coast (Italy). In Barruol et al. (2016), the authors evaluated the correlation between the polarization of the micro-seismic signal and the swell propagation direction. In Serafino et al. (2021), simultaneous measurements of a micro-seismic based system (called OS-IS) and those of a radar system were compared for the first

¹<https://www.datawell.nl/Products/Buoys.aspx>

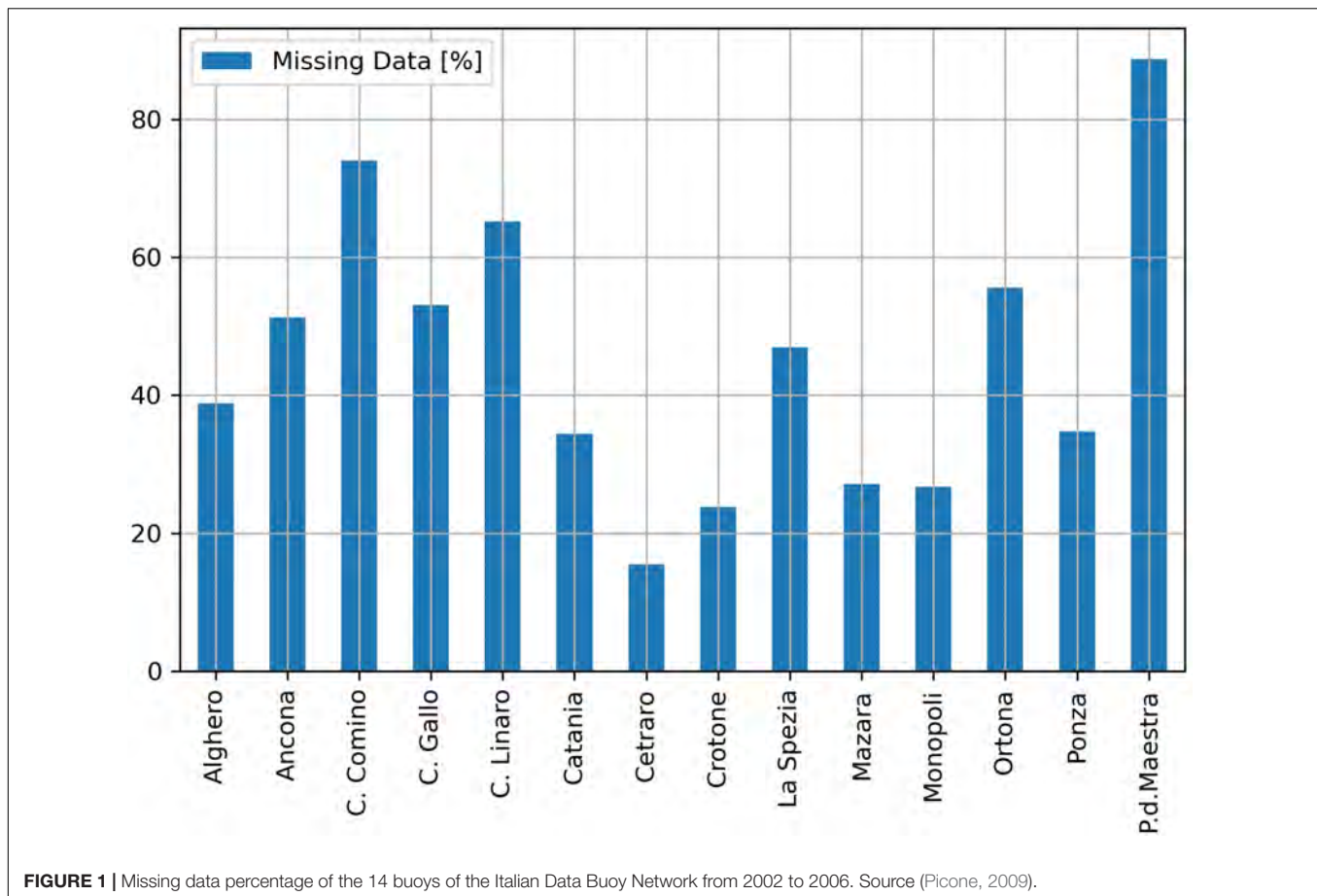


FIGURE 1 | Missing data percentage of the 14 buoys of the Italian Data Buoy Network from 2002 to 2006. Source (Picone, 2009).

time. In Cannata et al. (2020), a machine learning method (specifically, a random forest) was proposed to reconstruct the spatial distribution of sea wave height, as provided by hindcast maps of sea wave models, by using micro-seismic data from multiple seismic stations. In Moschella et al. (2020), a network of broadband seismic stations was used to investigate the micro-seismic signals from Ionian and Tyrrhenian Sea and, importantly, it was demonstrated that the signal detected by seismic stations closer to the sea contain more information concerning the sea state than the others.

As demonstrated in Iafolla et al. (2015), systems based on micro-seismic measurements outperform the systems based on moored buoys in terms of reliability and sustainability. Consequently in this work, we propose a measuring system consisting of a moored buoy, a micro-seismic measuring station, and a supervised machine learning algorithm to provide accurate sea wave measurements (specifically, significant waves height H_s , peak period T_p , and mean period T_m) continuously and reliably. This measuring system will typically provide the measurements from the buoy, which we will use as the desired output for the training data. Instead, the micro-seismic data are the input data, processed by the machine learning algorithms to reconstruct (i.e., “predict” in ML jargon) the sea wave data and fill the gaps due to the failures of the buoy. Therefore, the proposed system features the accuracy of the buoys and the reliability of the micro-seismic

method overcoming the limitations of the two methods taken separately. In this work, we present the methods to preprocess the data, develop the ML models, and evaluate their accuracy. As a case of study, we will use the data recorded simultaneously by a buoy and a micro-seismic based system to validate the proposed methods and to assess their accuracy.

BACKGROUND – FROM MICRO-SEISMIC SIGNALS TO SEA WAVES PARAMETERS

In this section, we introduce a simple model, based on the Longuet-Higgins’s one, to derive the sea waves parameters from the micro-seismic signals. This model provides basic notions and it was inspirational to develop the ML methods. Furthermore in this work, it was used as a benchmark for comparisons.

Longuet-Higgins showed that a peak of the micro-seismic spectrum is related to sea waves traveling in opposite direction (e.g., waves generated by coastal reflection) with similar frequencies. A peculiarity is that the peak of the micro-seismic spectrum has doubled frequency compared to that of the sea waves. Another phenomenon, with lower seismic energy and same frequencies as the sea waves, originates by the interaction of the waves with a sloping bottom. A recent review and detailed

description of these phenomena are given in Arduin et al. (2019). Considering the Longuet-Higgins phenomenon, a simple mathematical equation to calculate the significant wave height H_S from the micro-seismic power spectral density $S(f)$ (with f being the frequency) is the following (Bromirski et al., 1999).

$$H_S = \alpha \cdot \sqrt{\int_{f_{min}}^{f_{max}} S(f) \cdot df} + \beta \quad (1)$$

In the previous equation, α and β are parameters of the model. The limits of integration f_{max} and f_{min} are also parameters and define a bandwidth that must contain all the micro-seismic signal generated by the sea waves. However, this bandwidth should not be too large, in order to avoid extraneous micro-seismic contributions that would worsen the accuracy of the evaluation of H_S . To calculate T_m and T_p , one can simply use $S(f)$ in place of the sea wave power spectral density. However, we recall that the frequency of the micro-seismic signal is doubled compared to that of the sea waves. Therefore, T_p is $2/f_p$ (with f_p being the peak frequency of $S(f)$) and T_m is defined by the following mathematical formula (Krogstad et al., 1999).

$$T_m = 2 \cdot \frac{\sqrt{\int_{f_{min}}^{f_{max}} S(f) \cdot df}}{\sqrt{\int_{f_{min}}^{f_{max}} f \cdot S(f) \cdot df}} \quad (2)$$

MATERIALS AND METHODS

Measuring Systems

In this work, we used data collected in 2014 by a sea wave monitoring system, called OS–IS (Ocean Seismic – Integrated Solution), based on the micro-seismic method and data by the buoy of the Italian Data Buoy Network moored in proximity of La Spezia. The latter data are publicly available on the European Marine Observation and Data Network (EMODnet)² and a detailed description of the Italian Data Buoy Network is in Bencivenga et al. (2012). The buoy ISPRA-La Spezia was moored at latitude $43^{\circ}55'45.00''N$ and longitude $9^{\circ}49'40.00''E$ (see **Figure 2**). At about 16 km (green line), the OS–IS station was installed in the basement of Villa Pezzino, the INGV (National Institute for Geophysics and Volcanology) labs of Porto Venere (La Spezia), at latitude $44^{\circ}4'24.19''N$ and longitude $9^{\circ}50'22.84''E$.

The OS–IS station at INGV-Pezzino was installed in December 2013 in the framework of a project called Wind, Ports, and Sea (Bonino et al., 2015) funded by the European Cross-border Programme “Italy–France Maritime 2007–2013.” A detailed description of OS–IS is provided in Iafolla et al. (2014, 2015), Carmisciano et al. (2016) and its simplified schematic is shown in **Figure 3**. The core is the high-sensitivity three-axial accelerometer developed by AGI (Figure 4). Its background noise level is lower than 10^{-7} m/s²/√Hz in the bandwidth of interest for measuring the micro-seismic signal generated by the sea waves (from $\sim 4 \cdot 10^{-2}$



FIGURE 2 | Locations of La Spezia city (yellow marker), OS-IS station (INGV-Pezzino, green marker), and buoy ISPRA-La Spezia (green marker). The distance, indicated by the green line, between OS-IS and the buoy is about 16 km.

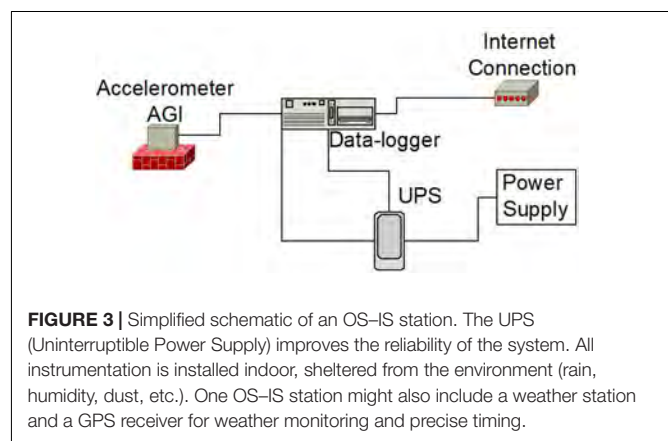


FIGURE 3 | Simplified schematic of an OS–IS station. The UPS (Uninterruptible Power Supply) improves the reliability of the system. All instrumentation is installed indoor, sheltered from the environment (rain, humidity, dust, etc.). One OS–IS station might also include a weather station and a GPS receiver for weather monitoring and precise timing.

to ~ 1 Hz). The sampling rate of the accelerometer was set to 10 Hz, which is about 10 times bigger than the highest frequency of interest. Although all three components (x , y , and z) of the acceleration were available, in this work, we used only the vertical component, aligned to the local gravity.

The measurements from the accelerometer were transmitted, through the internet, to a server for data storage and processing. Further descriptions regarding the computing system are reported in the section “Introduction” of **Supplementary Material** of this manuscript.

Graphical Tools and Validation Metrics for Data Analysis

In this work, data analysis was key for two main tasks. The first was to explore data, identify anomalies, and, consequently, remove noisy records. The second was to validate the ML models and assess their performance. The validation is done by

²<https://www.emodnet-physics.eu/map/platinfo/piroosplot.aspx?platformid=8712>

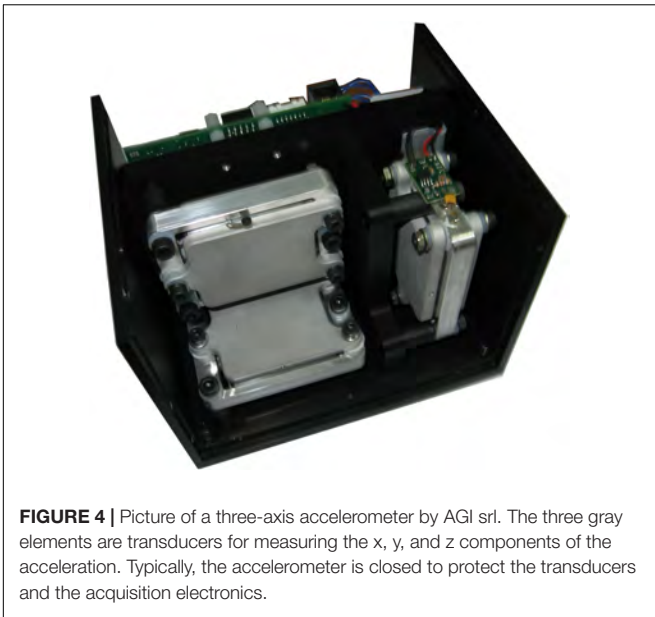


FIGURE 4 | Picture of a three-axis accelerometer by AGI srl. The three gray elements are transducers for measuring the x, y, and z components of the acceleration. Typically, the accelerometer is closed to protect the transducers and the acquisition electronics.

comparing two datasets: the predicted values and the desired values. For example, we compared the H_s values predicted by ML models and the H_s values measured by the buoy.

Performing the former tasks require several tools, both graphical and numerical. We used well-known graphical tools, such as time plots, scatter plots, and histograms, as well as less used (at least in sea wave to micro-seismic data analysis) tools such as empirical cumulative distribution function (ECDF) plots and hexagonal binning plots.

In ECDF plots (Downey, 2014), the value of the ECDF (y -axis) at any specified point x_0 of the x -axis is the fraction of observations of the variable x that are smaller than or equal to x_0 . In formula, $ECDF(x_0) = P(x \leq x_0)$, where $P(x \leq x_0)$ is the probability that $x \leq x_0$. ECDFs are useful for comparing sea wave distributions (Krogstad et al., 1999) because they smooth out random variations which, instead, are typical in histograms. Furthermore, synchronization of the records is not necessary, as with time plots, because the timing is lost in ECDFs.

Hexagonal binning plots are an alternative to the more common scatter plots to show and verify the relationship between two variables (Bruce et al., 2020). The records are grouped into hexagonal bins whose color indicates the number of records in that bin. The hexagonal binning plots are ideal to display large datasets that would appear as a monolithic cloud of points in conventional scatter plots. To make hexagonal binning plots, we used the *hexbin* function of the Matplotlib library of Python.

Other common methods for comparing two datasets are the validation metrics such as RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), and Pearson correlation coefficient (Géron, 2019; Bruce et al., 2020). To compute them, we used the functions *mean_squared_error*, *mean_absolute_error* (from sklearn.metrics library of Python) and *corrcoef* (from numpy library).

Data Pre-processing and Cleaning

Exploratory Data Analysis

Exploratory data analysis (EDA) is a process for gaining an insight into a dataset (Downey, 2014). A golden rule in ML is to always perform an EDA before preparing the data and feeding them into a ML algorithm. For example in this study, it is relevant to know how the values of H_s , T_p , and T_m are distributed and if there is any relationship between them. The section “Background – From Micro-Seismic Signals to Sea Waves Parameters” of the **Supplementary Material** reports the results of an EDA conducted on the dataset used in this study.

Data Augmentation

The amount and the quality of the training data is important for successfully training ML algorithms. In other words, a large dataset well representing the population of possible inputs is desirable. Sometimes, new training data can be generated from the available ones, this is called “data augmentation” in ML jargon. For example, it might be sufficient to flip one image about its central axis to obtain a new sample image for training. However, the new sample should not be too much alike the original one, otherwise it will not determine any improvement of the training.

In our work, the size of the dataset was limited by the sampling period of the buoy, which was 30 min. To increase this size, we interpolated the buoy data to a sampling period of 10 min. To do so, we used the *interpolate* method of the Pandas library of Python with the interpolation parameter set to “quadratic.” We did not further decrease the sampling period to avoid feeding the ML algorithms with samples too much alike each other. For example, records of the sea wave parameters are displayed in the time plots of **Figures 5A–C**. In such short timing, the variations are already quite small because of the inertia of the sea state. Consequently, further interpolation would not determine any improvement of the training because the newly generated records would be almost identical to the existing ones.

Feature Engineering

Data pre-processing is called “feature engineering” in ML jargon, where the features are the input variables of the algorithm: for example, if the input is an array, each of its elements is a feature. In other words, feature engineering defines the shape of the ML algorithm input and impacts significantly its performance (e.g., the accuracy). Inspired by the model introduced in the section “Background – From Micro-Seismic Signals to Sea Waves Parameters” and timeseries forecasting methods (Nielsen, 2019), we defined and tested two methods to engineer the features, i.e., to pre-process the micro-seismic data. Both these methods use the power spectral density (PSD) of the micro-seismic signal, like that shown in **Figure 6**. Details on the method to compute the PSD are provided in the section “Materials and Methods” of **Supplementary Material**.

We defined the first feature engineering method inspired by Equations 1, 2, which contain the micro-seismic spectrum $S(f)$. This method merely consists in using the PSD as ML algorithm input.

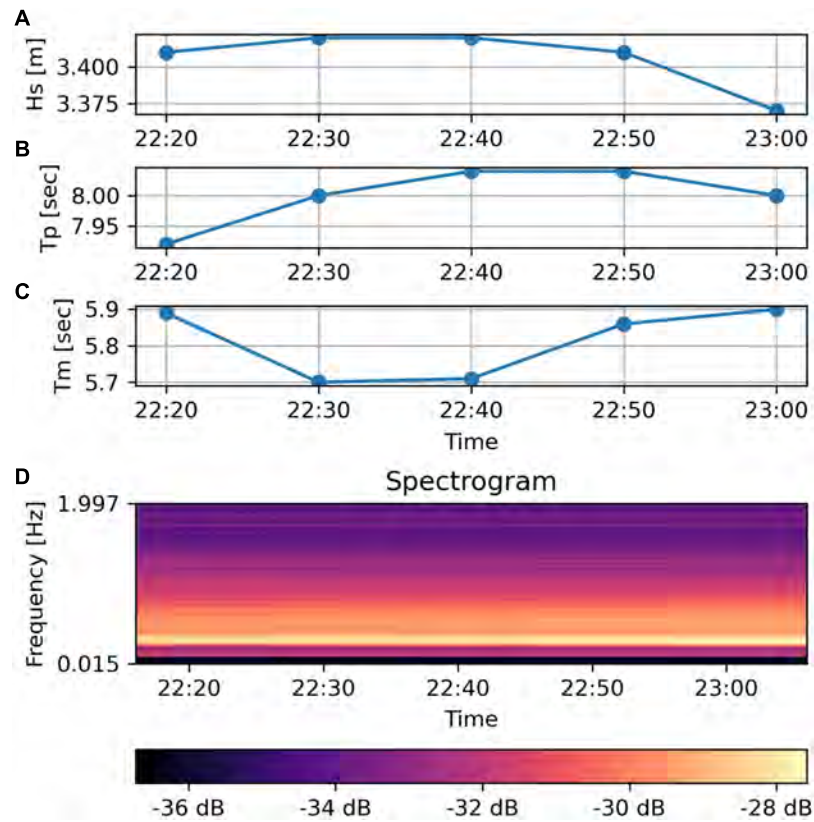


FIGURE 5 | The time plots (A–C) show five buoy records from 22:20 to 23:00 on the February 5, 2014. In (D) is shown the spectrogram of the micro-seismic signal, i.e., the five columns represent the five PSDs corresponding to the timings indicated by the labels on the x axis.

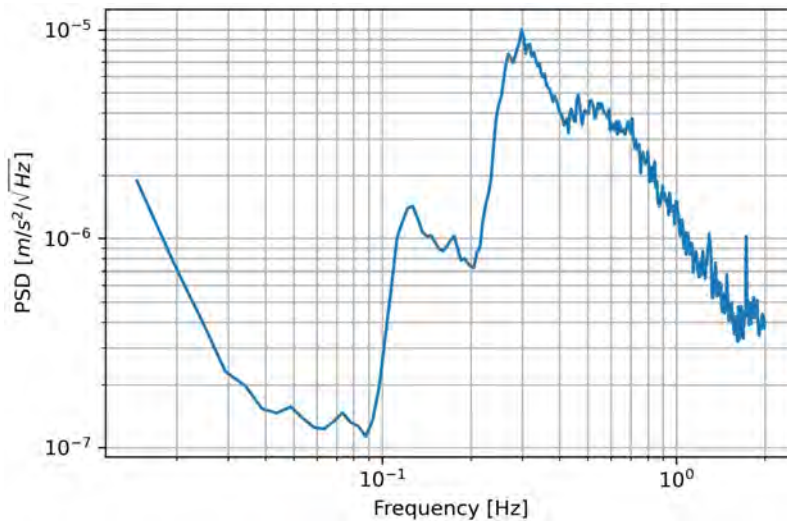
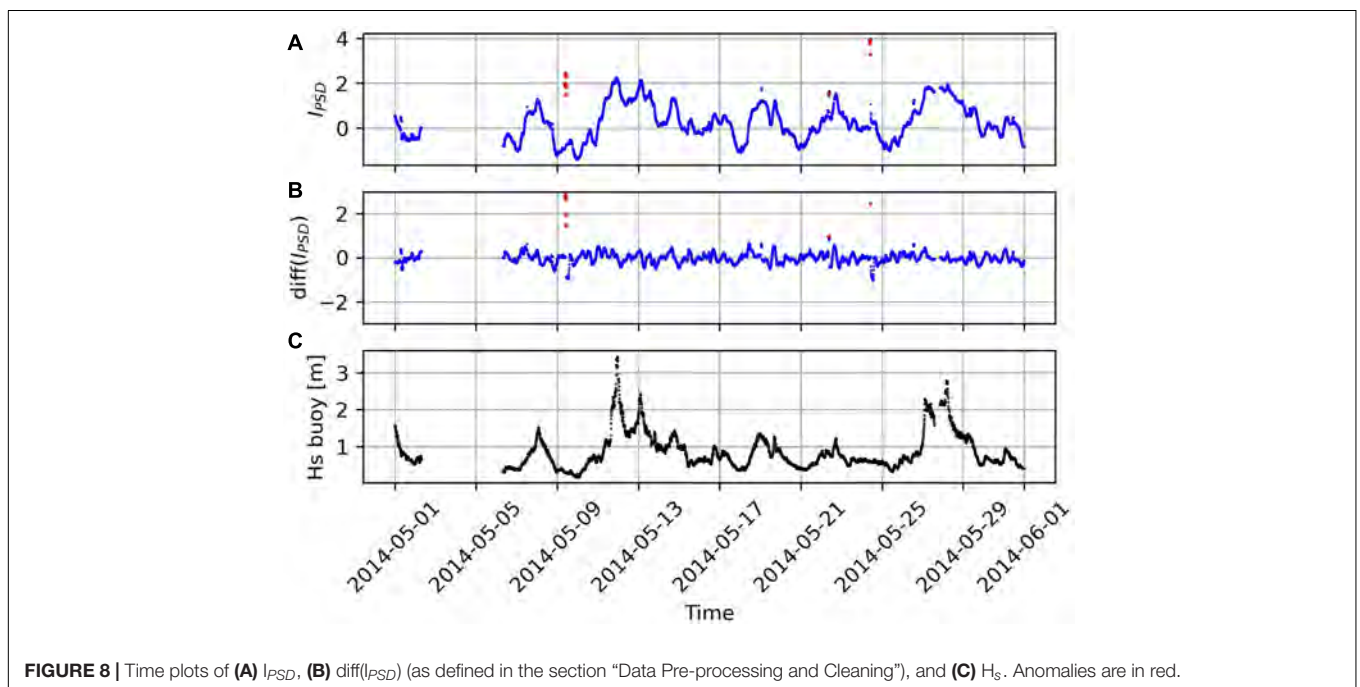
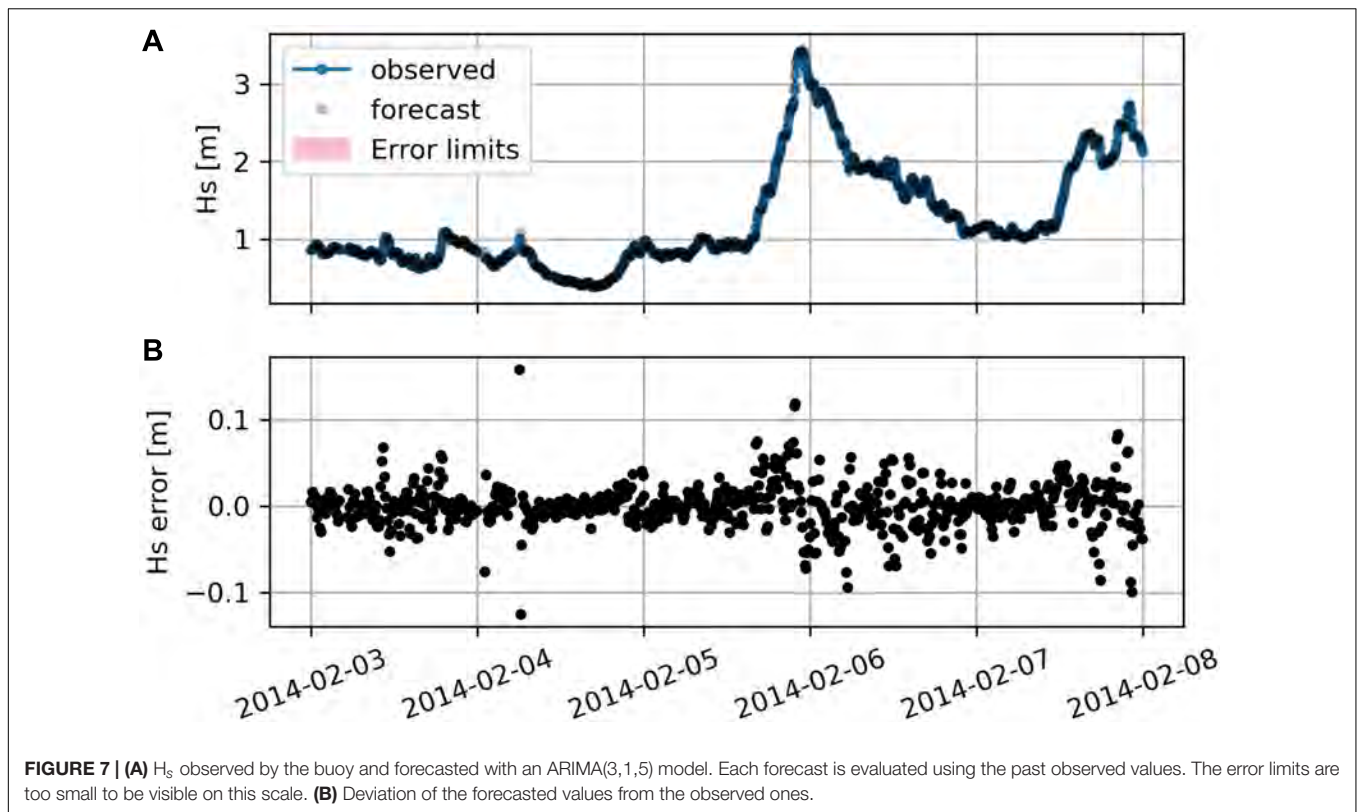


FIGURE 6 | Power spectral density (PSD) of the micro-seismic signal recorded on the February 5, 2014 at 23:00. The corresponding sea waves parameters from the buoy were: $H_s = 3.37$ m; $T_p = 8.00$ s; and $T_m = 5.90$ s.

We defined the second feature engineering method inspired by the analysis of the properties (stationarity, autocorrelation, partial-autocorrelation, etc.) of the timeseries H_s , T_p , and T_m and,

specifically, by the possibility to predict their present value from their past values (Nielsen, 2019). For example, **Figure 7** shows that an ARIMA(3,1,5) model can forecast H_s using its past five



values. This suggests that past H_s values carry useful information to evaluate the present value. Similarly, we supposed that the past records of the PSD might carry useful information to evaluate the present sea state. To leverage this, we used a spectrogram, i.e., an image combining the last five PSDs like that shown in **Figure 5D**,

as ML algorithm input. Similar spectrograms with more than five PSDs could be used, however they require more memory and computational power. More details on the computation of the spectrogram are provided in the section “Materials and Methods” of the **Supplementary Material**.

Summarizing, the first feature engineering method consists in feeding the ML algorithm with the present PSD of the seismic signal; the second in feeding it with the last five PSDs (i.e., the spectrogram).

Data Cleaning

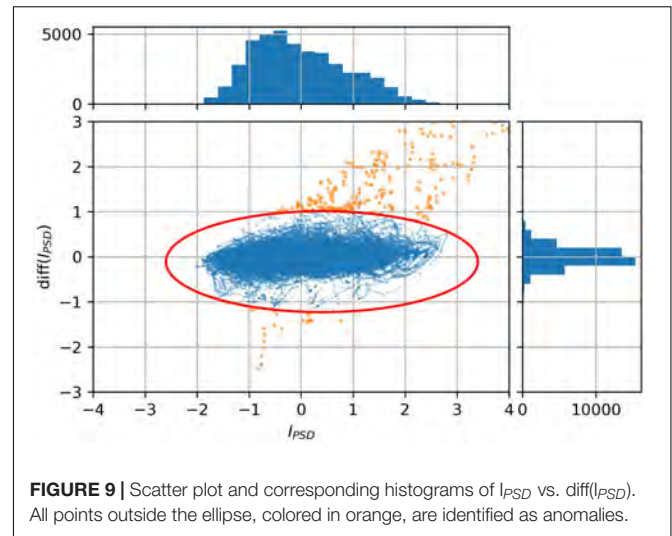
Data cleaning is aimed at achieving optimal results in ML and at checking the quality of the records during the operational use. Given the big amount of data and the real-time applications, it is also important to automatize the cleaning and the quality checking.

Data from the buoy were already classified with a quality check label (“good value,” “bad value,” etc.). We merely discarded all those samples whose label was not “good value.” Other records were dropped because the corresponding micro-seismic data were not available. The number of available and missing records is reported in **Supplementary Table 1**. In addition, we picked just the variables of our interest (i.e., timestamp, H_s , T_p , T_m , and swell direction) and dropped all other variables (e.g., temperature of the water, intensity of the wind).

To perform micro-seismic data cleaning, it was useful to compute a timeseries $I_{PSD}(t)$, or simply I_{PSD} , of the mean values of the elements of the PSDs. For example, $I_{PSD}(5^{th}$ February 2014 at 23:00) is the mean value of the points shown in the plot of **Figure 6**. For convenience, we standardized $I_{PSD}(t)$ by subtracting its mean value and dividing by its standard deviation. Furthermore, it was useful to compute the timeseries, $diff(I_{PSD})$, of the variations of each record of I_{PSD} with respect to the recent previous ones. To do so, we used a rolling window (4 h wide) technique over I_{PSD} ; i.e., $diff(I_{PSD})$ is the difference between the value of last point and the mean value within the window.

Using $I_{PSD}(t)$ and $diff(I_{PSD})$ we could identify noisy data caused by micro-seismic disturbances. Most common examples of the latter are earthquakes and human activities, such as people walking next to the accelerometer. These disturbances might last for several minutes and they might affect several consecutive input samples (i.e., PSD records). This is visible in the time plots of I_{PSD} , such that in **Figure 8A**. Bunches of points, highlighted in red, are clearly displaced away from the others, indicating an anomaly. Sometimes, these anomalies are very high and setting a threshold over I_{PSD} is sufficient to spot them automatically. An example is the bunch of points recorded on the 24th of May. However, their values are often lower than peaks due to the sea waves. For example, the bunch of red points recorded on the 9th of May are clearly anomalies because they do not have correspondence with the H_s measured by the buoy (**Figure 8C**). Still, their I_{PSD} values are lower than the peak on the 13th, which is due to sea waves. To automatically identify these points, we used $diff(I_{PSD})$, shown in **Figure 8B**, where these points emerge from the rest.

To automatically identify and discard anomalies, we made the scatter plot of I_{PSD} vs. $diff(I_{PSD})$ as shown in **Figure 9**. Most of the records are close to the center (0,0), as also visible from the side and top histograms, whereas the anomalies are far away. Consequently, we defined an ellipse (shown in red), inside which all good records are expected to be. The anomalies, colored in orange, are outside the ellipse and, consequently, easy to discard.



Defining the size and the position of the ellipse is trade-off: when it is too small, some good records might be wrongly discarded; when it is too large, some anomalies might not be identified as such. In our case, we defined the I_{PSD} axis length equal to 6 and the $diff(I_{PSD})$ axis length equal to 2.2.

Machine Learning Algorithms and Models Validation

Machine Learning Algorithms

The ML algorithms able to predict the sea state with the highest accuracy were ensembles of decision trees (bagging, boosting, and random forests) and convolutional neural networks (a special case of deep learning algorithms).

A decision tree (DT) (Géron, 2019; Bruce et al., 2020) is a process that sequentially examines, one per time, the features of an input sample assigning it to an output value. However, only a finite number of possible output values is defined during the training, consequently, the output is discrete.

Ensemble methods overcome the limit of the discrete output and improves the accuracy of the DTs. In general, an ensemble is a group of predictors, e.g., a DT, making predictions on the same input sample. The output of the ensemble is an aggregation, e.g., the average, of all predictions. There are several ensemble methods; we used bagging, boosting, and random forest (Random F.), which are among the most commonly used (Géron, 2019). We implemented the ensembles using the dedicated functions of the Scikit Learn library of Python and we fed them with the PSDs defined in the section “Data Pre-processing and Cleaning.” The most important parameters of the ensemble methods are the max depth of the DTs and the number of predictors (called $n_{estimators}$ in Scikit Learn). We used max depth equal to 7 and number of predictors equal to 15 or 20.

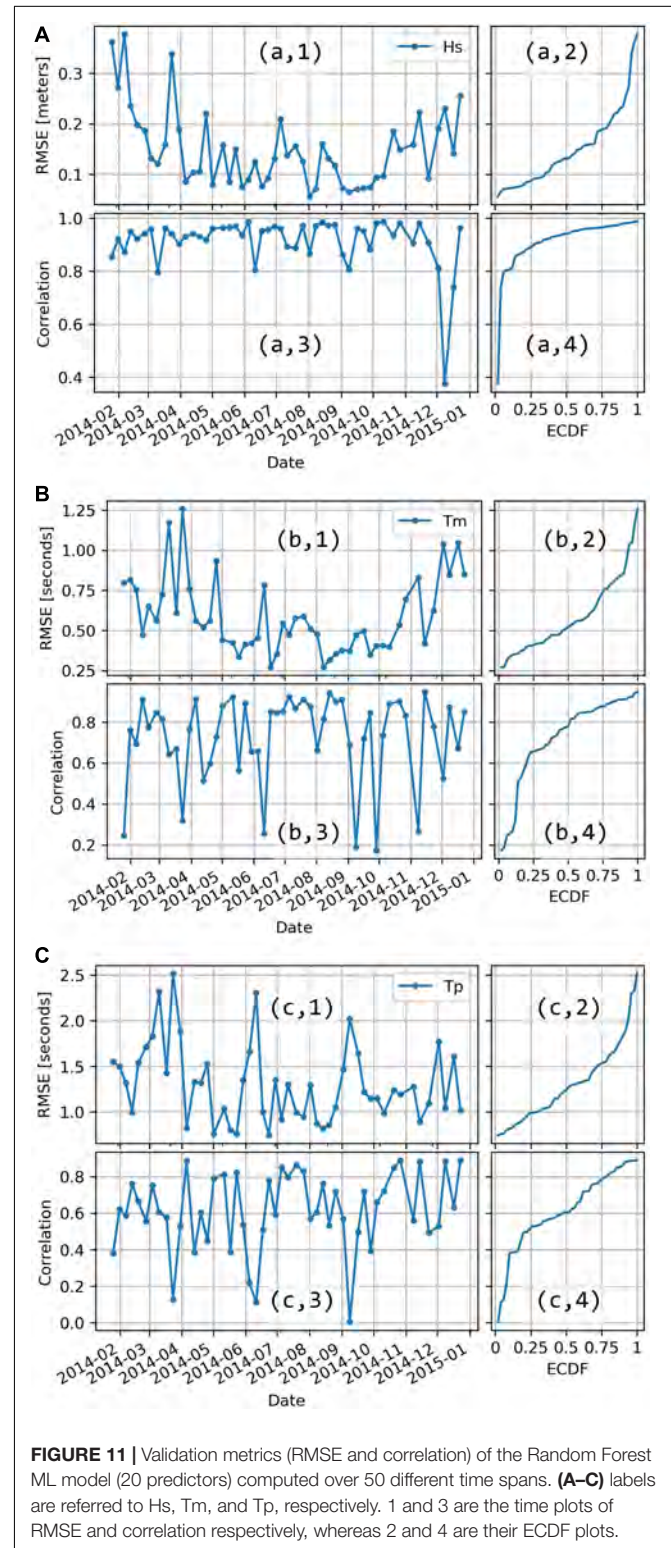
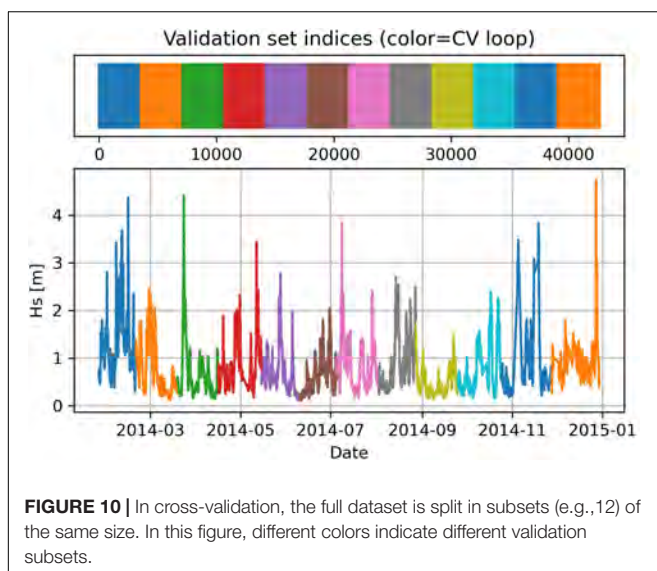
Finally, we trained and tested convolutional neural networks (CNNs), which were developed for processing images such as the spectrograms described in the section “Data Pre-processing and Cleaning.” For example, CNNs are famous for being able

to classify pictures of dogs, cats, or other objects. Adjusting their output layer, they can also make regression as needed for the sea wave variables. A CNN consists of several layers of different types that are stacked and set accordingly to the task (Géron, 2019). Very complex tasks usually require high number of layers, large training datasets, and the training takes very long time (or very large computational power). The configurations we tested in this work are reported in **Supplementary Table 2**.

Machine Learning Models Validation

After a ML algorithm has been trained using training data, it provides a ML model. This can predict the output given only the input data; however, its performance should be assessed before using it. To make this assessment, the graphical methods and the metrics introduced in the section “Graphical Tools and Validation Metrics for Data Analysis” can be used to compare the outputs of the model with the desired outputs. This assessment is called validation and it is performed over a validation dataset that must contain also the desired outputs. However, a ML algorithm might be able to memorize (this is called overfitting) the training data without being able to generalize over new input data. Therefore, keeping the training data separated from the validation data is key to validate correctly the ML model even when it is overfitting. One method is based on holding out a validation subset and training the ML algorithm by using the rest of the dataset. However, the validation results might depend on the chosen validation subset. To overcome this issue, we used a method called cross-validation (Géron, 2019; Bruce et al., 2020); the idea is to split the full dataset in subsets, e.g., 12 (see **Figure 10**). The ML algorithm is then trained 12 times, each time holding out a different subset and using it only for validation. Merging the results, we can obtain validation estimates over the full dataset. The bootstrap method (Bruce et al., 2020) can be used to assess the confidence intervals of the validation metrics. In this work, we used a similar method that allows us

to inspect the performance of the ML model over the time. The idea is to estimate the validation metrics over multiple (e.g., 50) consecutive time intervals. Specifically, first we divided the validation dataset in 50 consecutive subsets, then we estimated



the validation metrics of each subset to obtain a timeseries. This can be plotted to see how the ML model behaved over time and its ECDF can be used to easily assess the confidence intervals. Examples are shown in the section “Results,” **Figure 11**.

RESULTS

The dataset used for training and validating the ML models was made of 42603 simultaneous records, whereas 9957 records were not available or discarded during the data cleaning (see **Supplementary Table 1**, for more details).

The validation metrics of the best performing ML models and those of the conventional model introduced in the section “Background – From Micro-Seismic Signals to Sea Waves Parameters” (indicated as OS–IS Model) are reported in **Table 1, 2**. The OS–IS model is a good benchmark to assess the improvement achieved with the ML method because its performance was assessed using the same instrumentation and the same data. Rarely the OS–IS model performed better than the others, except for the MAE of T_p . The reason is that the OS–IS model was designed to provide measures of T_p only if H_s was larger than 1 m, when the signal to noise ratio was higher. To make a fair comparison, the last columns of **Table 1, 2** report the validation metrics of a ML model (Boosting 20 pred.) trained and validated using the same dataset as for the OS–IS model (i.e., featuring $H_s > 1$ m). As expected, its the validation metrics for T_p and T_m outperform those of the others, including those of the OS–IS model. This also highlights that the validation metrics depend on H_s and, more in general, on the training/validation data.

Comparing the ML models reported in **Table 1**, we notice that the difference between them is rather small, anyway, Random F. performed slightly better than the others on all metrics.

In **Figure 11**, the validation metrics (RMSE and correlation) are estimated 50 times over consecutive time intervals of about 1 week each (see “ML models validation” in the section “Machine Learning Algorithms and Models Validation”). Notice the high variability of the estimates. On the right side of each time

plot, the ECDF plots are shown and are useful to assess the confidence intervals. For example, in **Figure 11 (a, 2)** the median (ECDF = 0.5) of the RMSE estimates is ~ 0.13 m and 90% (ECDF = 0.9) of the RMSE estimates are smaller than ~ 0.25 m. Similarly, only 10% (ECDF = 0.1) of correlation estimates are smaller than ~ 0.8 .

Table 2 reports the validation metrics for a subset comprising only data from November to December 2014 (6229 records). Compared to the estimations in **Table 1**, the validation metrics are similar for H_s and T_p , but they are slightly worse for T_m . The same validation data are shown in **Figure 12** and **Supplementary Figures 5, 6**. Specifically in these figures, the predicted values of H_s , T_p , and T_m are compared to the desired outputs provided by the buoy. Inspecting these figures provides us with more insights than the validation metrics. For example, we notice that the absolute errors of H_s (**Figure 12B**), might be bigger than 1 meter (e.g., see the orange ellipse), but often this is due to a time-lag between the buoy measurements and predicted values. In fact, in subplot (a) we do not see a deviation bigger than 1 m between the buoy and predicted data (see the orange circle). Consequently, the MAE and the RMSE of H_s reported in the tables might be overestimated. On the other hand, histograms and ECDF plots do not suffer from the time-lag issue. For example, **Figures 12C,D** show a good agreement between buoy and predicted data. On the opposite, histograms and ECDF plots (c) and (d) of T_p and T_m in **Supplementary Figures 5, 6** do not overlap as nicely as with H_s . This indicates that assessing accurately T_p and T_m is slightly more complex than assessing the H_s .

Inspecting the errors histograms [subplots (e)] is a good way to evaluate if the ML model is introducing a systematic error. In fact, this would skew the histogram or displace its center away from zero; however, such effects were not detected in our case.

Finally, **Figure 13** shows the hexagonal binning plots of the predicted values vs. the desired values from the full dataset. Each plot also shows a black straight line along which the points are expected to align in the ideal case. We notice that for H_s [subplot (a)], the points are mainly concentrated next to the black line for values smaller than 2 m whereas they are more spread for bigger values. However, the hue also indicates that

TABLE 1 | Performance of the ML models trained and validated over the data from 2014.

Algorithm	Random F. 20 pred.	Boosting 20 pred.	Boosting 15 pred.	Bagging 15 pred.	CNN Config. 1	CNN Config. 2	OS-IS Model	Boosting 20 pred.
Dataset	Full dataset							$H_s > 1$ m
RMS H_s [m]	0.17	0.18	0.18	0.17	0.19	0.23	0.21	0.24
MAE H_s [m]	0.11	0.12	0.12	0.11	0.14	0.15	0.14	0.17
Corr H_s	0.95	0.95	0.95	0.95	0.94	0.93	0.93	0.89
RMS T_p [s]	1.38	1.38	1.38	1.38	1.40	1.47	1.52*	0.97
MAE T_p [s]	0.98	1.01	1.01	1.00	1.03	1.09	0.96*	0.68
Corr T_p	0.72	0.72	0.72	0.72	0.71	0.67	0.56*	0.78
RMS T_m [s]	0.63	0.63	0.64	0.65	0.70	0.66	0.95	0.57
MAE T_m [s]	0.44	0.45	0.46	0.46	0.52	0.48	0.67	0.41
Corr T_m	0.83	0.83	0.82	0.82	0.81	0.82	0.65	0.82

Notice that, the ML model on the last column was trained only with data satisfying the condition $H_s > 1$ m. The best performances are in bold. *The validation of OS-IS Model over T_p was performed only for $H_s > 1$ m.

TABLE 2 | Performance of the ML models trained over the data from 2014 and validated over the data from November to December 2014 (6229 records).

Algorithm	Random F. 20 pred.	Boosting 20 pred.	Bagging 15 pred.	CNN Config. 2	OS-IS Model	Boosting 20 pred.
Dataset	November – December 2014					$H_s > 1$ m
RMS H_s [m]	0.19	0.20	0.20	0.23	0.24	0.23
MAE H_s [m]	0.13	0.13	0.14	0.16	0.17	0.15
Corr H_s	0.95	0.95	0.95	0.92	0.93	0.95
RMS T_p [s]	1.28	1.30	1.27	1.32	1.47*	1.10
MAE T_p [s]	0.95	0.98	0.96	1.00	0.98*	0.80
Corr T_p	0.78	0.77	0.78	0.76	0.65*	0.80
RMS T_m [s]	0.83	0.79	0.84	0.80	1.13	0.73
MAE T_m [s]	0.60	0.58	0.62	0.61	0.82	0.52
Corr T_m	0.80	0.82	0.79	0.81	0.63	0.81

Notice that, the ML model on the last column was trained only with data satisfying the condition $H_s > 1$ m. The best performances are in bold. *The validation of OS-IS over T_p was performed only for data with $H_s > 1$ m.

values bigger than 2 m are much less frequent; consequently, the ML algorithm is less exposed to those values during the training, leading to worse accuracy. The spreading of T_m and T_p , subplots (b) and (c), is not significantly larger for bigger values. However, we noticed that the points of T_p [subplot (c)] do not distribute symmetrically about the black straight line, particularly for values between 2 and 4 s (inside the yellow circle). Most likely, this is driven by those records whose $H_s < 1$ m. In fact, when the signal to noise ratio is lower (i.e., $H_s < 1$ m), it is harder to identify the peak frequency (i.e., the peak period) than when the signal to noise ratio is higher (i.e., $H_s > 1$ m). This agrees with the validation metrics reported in the last columns of **Table 1, 2**.

DISCUSSION

The objective of this work has been to develop a sea wave monitoring system consisting of a moored buoy, a micro-seismic station, and a ML algorithm to automatically reconstruct missing buoy data using micro-seismic data. In this section, we discuss many aspects that differentiate our work from previous ones in the same field.

To begin, reconstructing missing buoy data using micro-seismic data is a novel aspect as, in previous works, other types of input data were used. For example, offshore hindcast and wind information were used in Vieira et al. (2020) and weather data of adjacent buoys and bathymetric data were used in Jörges et al. (2021). Moreover, many works were limited to short term (less than 48 h) predictions meaning that their models rely on recent observations of the buoy, e.g., (Agrawal and Deo, 2002). Instead, the proposed system can make predictions for any time after the last buoy observation keeping the same level of accuracy. This is key as buoy data gaps might be several weeks long.

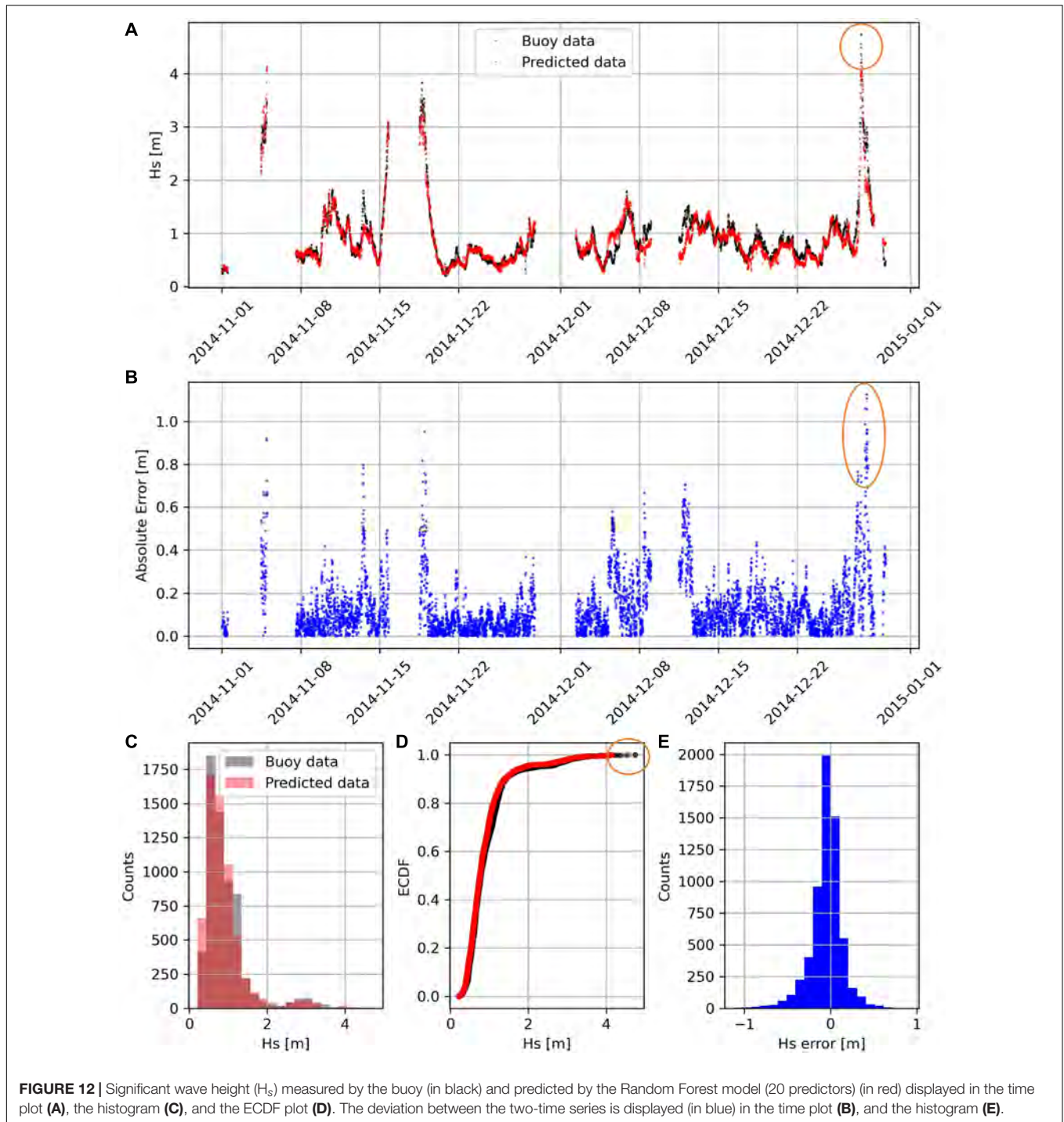
As reported in the section “Introduction,” several previous works investigated the methods to retrieve sea wave data from micro-seismic data. A key aspect of the present work is the application of ML to automatically find the -micro-seismic to sea waves relationship- directly from data, with no need to develop

and calibrate complicated geophysical models. Furthermore, the more training data are collected during the operations, the more accurately the ML model can perform. For example, by routinely training the ML algorithm as soon as new data is available, new types of events will be incorporated in the ML model with no need of manually tweaking its parameters, e.g., as in Cutroneo et al. (2021). Despite these many advantages, ML limits the investigation on the input-output relationship (i.e., on the geophysical phenomenon) because most of the ML algorithms are “black boxes.” Although this would be limiting in projects whose objective is to investigate the geophysical phenomenon, e.g., (Ardhuin et al., 2011), it is not relevant for missing data reconstruction.

Many aspects of the system were defined accordingly to the objective. For example, the micro-seismic station used for this work was specifically installed close to the shoreline and in front of the buoy of La Spezia (see **Figure 2**). As demonstrated in Moschella et al. (2020), this displacement of the instrumentation leads to more accurate buoy data reconstruction. In fact, undesired signals, such as those from remote seismic sources, are less relevant and the signal to noise ratio is higher than that of stations far away from the shoreline and the reference buoy. For example in Ferretti et al. (2013), the micro-seismic stations were from previous projects with different purposes (e.g., seismic monitoring) and, due to their locations, the interpretation of the signals was more complex.

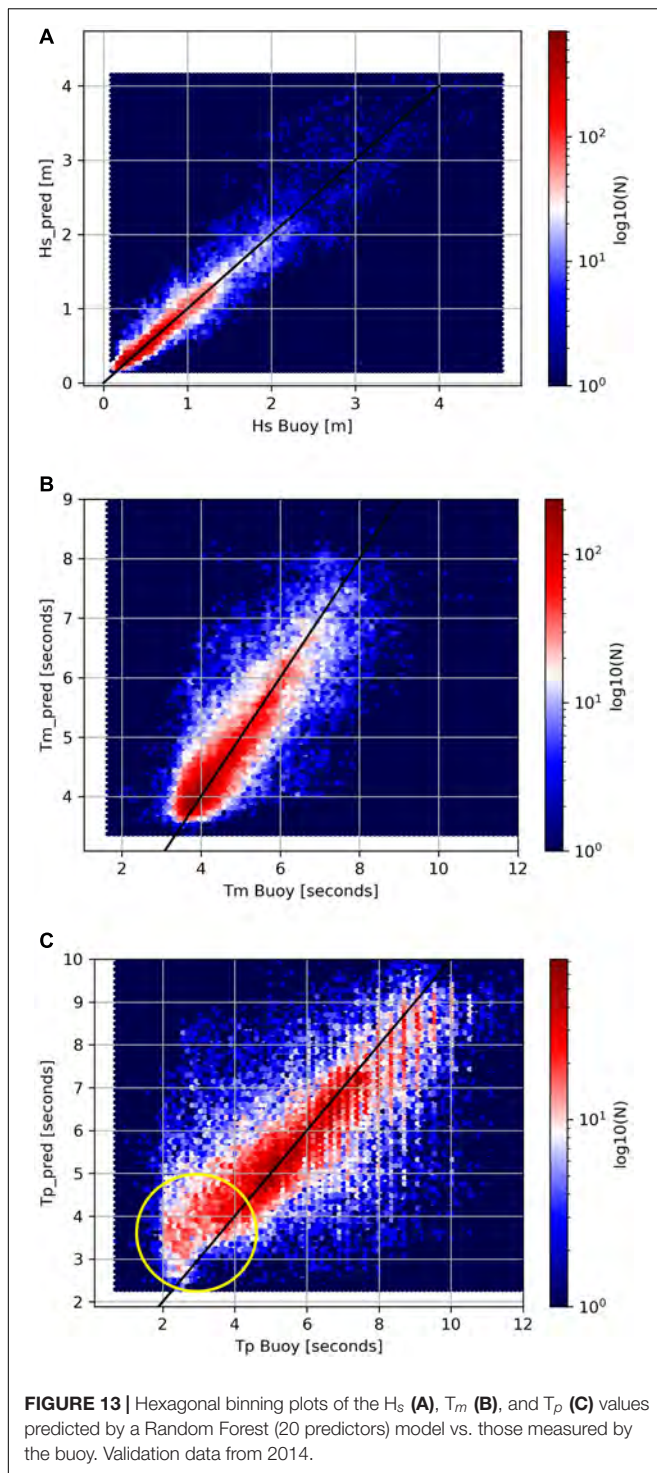
Pursuing our objective, it was also important to use buoy data to train the ML algorithm and not weather model data, e.g., as done in Cannata et al. (2020). In fact, if the sea wave data from weather models were a ground truth, there would be no need to retrieve the same data from any monitoring system. On the opposite, sea wave monitoring data are critical to validate weather models and implement data ingestion techniques.

In the section “Materials and Methods,” we have gone through the main steps of the data processing; these are the typical steps of a ML project. Data cleaning is very important because ML algorithms are very sensitive to outliers and noisy data: the proposed method to clean the micro-seismic data is quite



standard but still very effective; furthermore, it can be used to check the quality of the results during the monitoring operations. Despite the importance, data cleaning methods were seldom discussed in previous works. Feature engineering typically impacts the overall performance of ML models. We proposed two methods: one is based on using PSD arrays, the other on spectrograms; the latter was specifically meant for CNNs. Then, we introduced some ML algorithms and assessed

their performance. Random forest was the best performing while CNNs did not shine as expected. Notice that the method to estimate and validate sea wave periods (T_p and T_m) from the micro-seismic data was discussed. This was often disregarded in previous works and the validation of waves period estimates was rarely presented. Still, the waves period is an important parameter to assess the energy and, consequently, the impact of the sea waves.



We have shown that the performance assessments, in particular the validation metrics, depend on the validation dataset. For example, the periods are better evaluated when H_s is bigger than 1 m; this should not be surprising because the signal to noise ratio is higher. To avoid wrong performance assessments, we proposed to use cross-validation, which is rarely used in projects related to the calculation of sea wave data

from micro-seismic signals. Furthermore, we proposed a method to evaluate the confidence interval of the validation metrics using their ECDFs.

Our results for the accuracy on H_s estimates are comparable to those of other works. However, accuracy depends on many variables (e.g., validation dataset, measurement site, sea wave conditions, and time interval length) that make such comparisons meaningless. Consequently, the accuracy estimations should be used only to assess the ability of the system to reconstruct the missing buoy data.

It is worth to stress that the proposed system is an improvement of an existing technology for sea state monitoring, i.e., that of moored buoys. Accordingly, the micro-seismic system is not meant to operate as a standalone device. Therefore, the buoy is expected to continuously provide training data, particularly of sporadic events such as rare storm events; once these are incorporated in the training dataset, the ML algorithm will learn how to reconstruct them from the micro-seismic data. On the opposite, if the buoy is dismissed at some point in time, some new sporadic events might occur and the ML algorithm would not be able to reconstruct them accurately.

Finally, we stress the value of data science methods that are poorly and seldomly used in studies related to the evaluation of sea wave data from micro-seismic signals. Besides the ML methods, we have shown methods to compare timeseries and distributions. These are key when comparing and validating complex data such as sea wave measurements. For example, conventional scatter plots were often shown, where points formed a monolithic cloud hiding most of information. Instead of scatter plots, we proposed to use hexagonal binning plots. The validation metrics, such as RMSE, MAE, and correlation, were typically reported but, although very useful, they rarely tell the whole story. Instead, tools such as the ECDF plots were rarely used despite they are more informative than validation metrics.

CONCLUSION

In this work, we introduced a novel sea state monitoring system able to automatically reconstruct missing buoy data using micro-seismic data and machine learning. Specifically, we presented the methods to process the data, develop and train the ML algorithms, and assess their accuracy. As a case of study, we used the data collected in 2014 from a buoy of the Italian Data Buoy Network and a micro-seismic station (OS-IS). We demonstrated that many ML algorithms were able to reconstruct H_s , T_m , and T_p . However, the best performing was a Random Forest algorithm, whose root mean squared errors of H_s , T_m , and T_p were, respectively 0.17 m, 0.63, and 1.38 s. When H_s was bigger than 1 m, the accuracy of T_m and T_p improved to, respectively 0.57 and 0.97 s.

By collecting more data, particularly for rare storm events, and tweaking the ML algorithm architectures, we believe that the accuracy can further improve. Specifically, we believe that the full potential of the CNN and the spectrograms as input, was not fully

exploited. To do it, spectrograms with larger time span should be used and the CNN models should be more complex (i.e., more parameters). However, this requires more computational power than that available for this work.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, the micro-seismic data are available upon request to the authors. Further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

LI: conceptualization, methodology, software, validation, investigation, writing – original draft, writing – review and editing, and visualization. EF: validation, investigation, writing – review and editing, and supervision. MC: writing – review and editing, supervision, project administration, and funding acquisition. CC and VI: conceptualization, methodology, validation, investigation, writing – review and editing, supervision, project administration, and funding acquisition.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fmars.2022.798167/full#supplementary-material>

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Conflict of Interest: LI and EF are employed by AGI srl. AGI srl commercializes products and has filed a patent (still pending in January 2022) relevant to the system presented in this work.

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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