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New developments in the Praia da Vitória Coastal Bay and Harbor Early Warning System

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ABSTRACT: The disruption of port operations, whether due to technical issues or external factors, can have a significant impact on the port's overall competitiveness and economic viability. The HIDRALERTA Early Warning System is operational on a daily basis, issuing emergency alerts concerning wave overtopping, ship navigation, and operational constraints for seven ports and coastal zones in mainland Portugal, as well as three additional ports in the Azores Islands. The system is designed to enhance port resilience by mitigating potential risks through improved planning and swift emergency responses. The system employs a suite of numerical models that utilise forecasts of regional wind and sea-wave characteristics offshore, along with astronomical tidal data, as inputs. These numerical models generate estimates of wave and wind characteristics at both regional and local scales. Furthermore, the system computes the ship's response to these wave and wind forces using a hydrodynamic 3D model and a motion equation solver. Currently. the HIDRALERTA system is being extended to incorporate new methodologies. This paper presents a case study to demonstrate the aforementioned developments at the port of Praia da Vitória, situated on Terceira Island, and its adjacent coastal bay. A notable advancement is the use of artificial neural network tools to enhance wave predictions at certain locations where extensive historical data are available.

KEYWORDS: Early warning System, Neural Networks, Flood risk, Navigation

1 INTRODUCTION

The extensive coastline of Portugal, which extends to approximately 1,860 kilometres, including the mainland and the Azores and Madeira archipelagos, is frequently exposed to emergency situations arising from storms and adverse sea conditions. These coastal hazards present a significant threat to public safety, maritime structures, infrastructures, and port activities. Given the high exposure of the coastline to severe storms and hurricanes, especially in the Azores islands, which have a long history of such incidents, it is crucial to understand and predict the risks associated with wave-induced overtopping, flooding, and navigation challenges. In this context, it is evident that early warning systems (EWSs), play an important role.

The initial attempts to develop EWSs for extreme ocean-related events were primarily focused on coastal areas and parameters such as currents, sea levels, and flooding (Gracia et al. 2014). These endeavours frequently drew upon limited data sources (Doong, et al. 2012).

Some EWSs employ a simplified approach based on empirical equations (Stokes, 2021) or on offline simulations (a limited set of pre-run scenarios), thereby lacking the modelling of complex physical phenomena (Lane et al. 2008; van Dongeren et al. 2018; Garzon et al. 2022). In contrast, more sophisticated systems use real-time complex numerical simulations to generate more precise forecasts (Gracia et al., 2014, Auclair 2022). However, certain systems still concentrate on parameters such as currents, sea level, temperature, waves or salinity fields (Trotta et al., 2021; Moore et al. 2021; Leitão et al., 2023). This approach may lack specificity in quantifying the actual risks faced by port infrastructure or fail to provide timely warnings.

An effective Early Warning System (EWS) is defined as a system that is capable of predicting the occurrence and severity of hazards. Such a system ultimately reduces a port's vulnerability by enhancing its capacity for planning and efficient response to emergency situations.

In order to achieve this objective, the system must: a) be underpinned by robust data concerning meteorological, oceanographic, and geological conditions; b) provide accurate forecasts of critical parameters, using suitable numerical models and statistical techniques; c) communicate warning information to coastal/port stakeholders and communities in a timely and effective manner; d) educate stakeholders and coastal communities about potential hazards and develop comprehensive evacuation plans.

However, reliable data on coastal met-ocean conditions are scarce and confined to a few locations where buoy measurements are available, often subjected to flaws primarily due to inoperability periods.

Moreover, the complexity of atmospheric and oceanic systems makes it extremely challenging to forecast wave and wind conditions, their transformations, and the intensity of the ensuing coastal hazards. EWS heavily depend on the quality of the offshore data and of the numerical models upon which they are built.

The case study presented in this paper, which illustrates these developments, is the port of Praia da Vitória, located on Terceira Island, and its adjacent coastal bay.

A recent enhancement to the system involves the application of neural network tools to calibrate the wave propagation models. As with any EWS, its effectiveness is significantly influenced by its reliability and accuracy (Dominguez & Resio, 2016).

In order to achieve more accurate predictions, a new method was developed with the objective of optimising the forecasts produced by the system.

The use of data from available databases encompassing buoys, pressure sensors, and meteorological stations enabled the application of neural networks to enhance the accuracy of the numerical models' results.

2 EARLY WARNING SYSTEM

2.1 Development and Scope

In recent years, a number of serious incidents involving moored ships and navigation have occurred in various ports and coastal areas of the Azorean islands. In response, the port authority, *Portos dos Açores, SA*, recognised the necessity for an EWS capable of forecasting waves, overtopping, flooding, and navigation risks, particularly those associated with moored ships and the navigation of access channels. Consequently, the development of this system was initiated for the ports of Praia da Vitória S. Roque do Pico and Madalena do Pico.

The HIDRALERTA system retrieves daily 72-hour wave and wind forecasts from the European Centre for Medium-Range Weather Forecasts and Copernicus, with intervals of either 3 or 1 hour, to drive the wave module and operates in real-time mode.

The selection of the time interval is contingent upon the specific requirements of the prototype. For instance, erosion estimation within the system utilises a 1-hour interval, a practise that is also being implemented for the system's ongoing expansion to include ship manoeuvring simulations. Presently, for the prototypes at the ports, a 3-hour interval is employed due to the constraints of computational resources. The decision to utilise a 1-hour interval is typically straightforward, contingent upon whether employing a three-hour interval might yield less accurate results by failing to fully capture the tidal influence.

The simulated incident wave conditions at the toe of the structures/ships, along with other met-ocean parameters such as wind, currents, and sea level, are used to compute wave overtopping and ship motions. As all numerical models operate in real-time, modifications to the initial data or boundary conditions (such as bathymetry, structures) can be readily implemented.

The HIDRALERTA system has previously assisted local entities in Praia da Vitória before and during the passage of Hurricane Alex over the Azores islands. It is noteworthy that the system was able to identify the low-pressure atmospheric system from which that hurricane developed a week in advance. The tools provided by the HIDRALERTA system, in conjunction with the expertise and experience of local entities, facilitated the decision-making process regarding risk prevention and minimisation measures.

One of the most notable features of HIDRALERTA is its capacity to issue alerts for overtopping and induced flooding in coastal areas and harbours, as well as for moored ships within the port or harbour. Typically, port activities such as ships' approach manoeuvres and loading/unloading operations, are conditioned or suspended based on weather or wave forecasts, often leading to significant economic losses. Nevertheless, there are instances when dire weather forecasts result in minimal distress, and severe accidents frequently occur under nearly average wind and wave conditions. Furthermore, the effects of excessive mooring forces on ships can be effectively managed with an appropriate or reinforced mooring arrangement if their effects on the ships can be accurately forecasted. A precise risk assessment must rely on specific parameters that are directly related to the actual risks being predicted. These include overtopping discharges or volumes, as well as the movements of the ship and its mooring loads. In order to accurately predict the aforementioned risks, it is essential to consider the entire wave-structure interaction system or the wave-moored ship interaction system. This specifically renders the

HIDRALERTA system a unique and valuable asset. Furthermore, it is becoming an increasingly effective tool to establish, implement, and monitor emergency plans, thereby supporting authorities in managing hazardous situations. Moreover, the system serves as a long-term management tool, as it is capable of simulating responses to future scenarios related to climate change. These scenarios may include increases in mean sea level and/or storm severity, which are likely to elevate the possibility of coastal flooding.

The HIDRALERTA EWS (Figure 1) encompasses three Azorean ports: Praia da Vitória, São Roque do Pico and Madalena do Pico, (ECOMARPORT project), and six mainland ports: Ericeira (To-SEAlert project), Costa da Caparica (To-SEAlert project), Sines (BLUESAFEPORT project), Peniche (BSafe4Sea project), Faro and Quarteira (EW-Coast project).

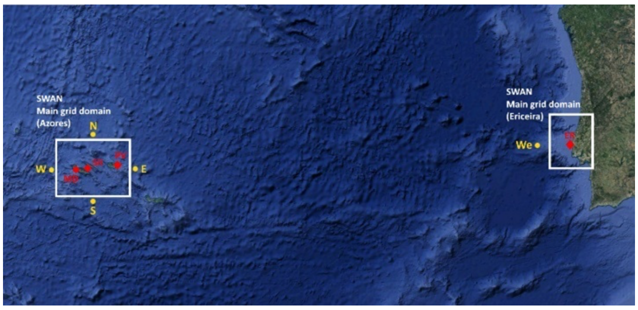

Figure 1. HIDRALERTA EWS pilot sites in Azores and mainland Portugal.

The case study presented in this paper concerns the Praia da Vitória coastal bay and harbour, Figure 2. Praia da Vitória is a small town situated along the eastern coast of Terceira Island, which forms part of the Azores archipelago. The bay and harbour of Praia da Vitória are of significant economic importance to the island of Terceira. The bay's deep, sheltered waters provide an optimal environment for a diverse range of maritime activities, including fishing, commercial shipping, recreational sailing, and yachting. The harbour is home to the island’s sole container ship quays and a substantial fishing fleet. To the north of the bay, a marina caters to pleasure crafts, while an expanding maritime tourism sector is also in evidence.

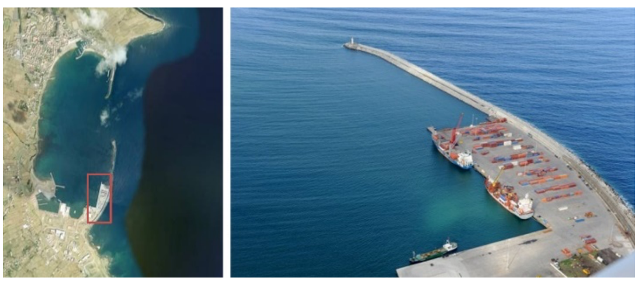

Figure 2. Praia da Vitória Bay and harbour (left). Container terminal (right).

2.2 Structure of the EWS

The Early Warning System (EWS), known as HIDRALERTA, Pinheiro *et al.* (2020, 2022), operates on a daily basis to provide emergency alerts related to wave overtopping and ship navigation, as well as operational constraints of port activities across seven ports and coastal zones in mainland Portugal and three additional ports in the Azores Islands.

The HIDRALERTA system employs a combination of numerical models that run in real-time to simulate wave propagation, estimate mean overtopping discharge over port infrastructures and coastal defence structures, and determine the motions and mooring forces of ships. The system employs available forecasts of regional wind and sea-wave characteristics offshore, in conjunction with astronomical tidal data as inputs to the numerical models. These generate forecasts of overtopping volumes, movements, and mooring forces on a three-hour basis, which are subsequently compared with pre-set thresholds. The probability assessment of exceeding these thresholds facilitates risk level assessment. Based on the forecasted risk level, potential emergency situations, and the safety of port operations can be foreseen in advance (72h), thus allowing for the issuance of adequate warning alerts.

Any modifications to the initial data or boundary conditions, such as bathymetry or structural details, can be readily incorporated.

In accordance with the recommendations set forth by Basher (2006) & the ISDR Platform, an effective and comprehensive early warning system comprises four essential elements: Risk knowledge, Monitoring and warning service, Dissemination and communication, and Response capability.

The current architectural framework of the HIDRALERTA system, Figure 3, prioritizes the Monitoring and warning service (modules I to IV), and the Dissemination and communication (Module V) elements.

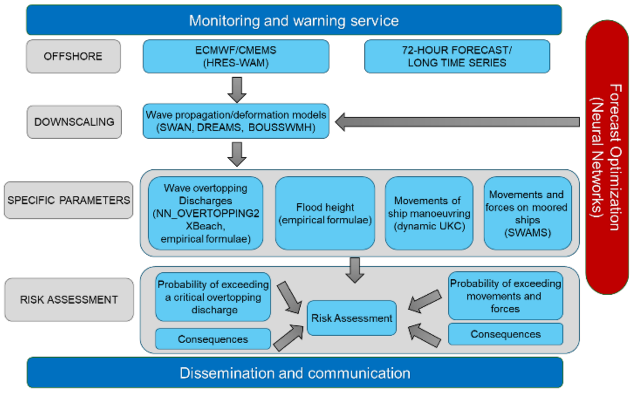

Figure 3. The HIDRALERTA EWS architectural framework with NN modelling.

Module I – Forcings. In this module, the characteristics of the sea-waves, as well as water levels and wind conditions, are defined. Offshore wave conditions (either hindcast or forecast data) are provided by the ECMWF and CMEMS and are propagated inshore using the SWAN model (Booij et al., 1996). While inshore wave conditions can be directly applied to coastal applications, specific models are required for ports. In such instances, HIDRALERTA employs either the DREAMS model (Fortes, 2002) or BOUSSWMH (Pinheiro et al. 2011). A more detailed explanation can be found in sections 3.1 and 3.2.

Module II – Specific parameters. The sea conditions delineated in Module I serve as an input to estimate:

i) Wave overtopping over port structures with NN_OVERTOPPING2 (Coeveld *et al.*, 2005), with ongoing enhancements incorporating SWASH (Zijlema *et al.*, 2011).
ii) Flood height at natural beach profiles based on empirical formulas derived from physical model tests by Hunt (1959) and field data (natural beaches) by Holman (1986), Stockdon et al. (2006), Nielsen and Hanslow (1991), Ruggiero et al. (2001), Guza and Thornton (1982) and Teixeira (2009). The values obtained from the aforementioned formulas are evaluated for consistency. In the event that no discrepancies are identified, the results are averaged and combined with the tide level and storm surge to determine the flooding height.
iii) Wave overtopping over coastal structures with empirical formulae from Mase *et al.*, (2013) and Masatoshi *et al.* (2019), which are based on physical model tests, are employed for structures situated in proximity to or along the coastline. For certain prototypes, HIDRALERTA integrates simulations from XBeach (Roelvink *et al.*, 2009) with Bayesian networks to enhance accuracy.
iv) For the calculation of forces on mooring lines and fenders, as well as ship motions at quays, the SWAMS software (Santos, 1994, Pinheiro *et al.*, 2013) is employed. More details are given in Section 3.3.
v) Ship manoeuvring safety (through the evaluation of dynamic under-keel clearance along the ship route while entering the port).

Module III – Forecast optimization. In this module, neural networks are trained to enhance the accuracy of numerical wave prediction models (as detailed in section 4) at inshore locations using data from wave buoys.

Module IV – Risk assessment. Comparison of the computed values generated in Module II (overtopping discharge, flood height, ship movements, mooring forces, and under keel clearance) against pre-set thresholds, with the objective of issuing warnings. The risk levels are classified into four distinct categories (from 0 to 3, where 0 indicates no risk and 3 represents the highest level of risk). Further details on the assessment of risk for moored ships can be found in Section 3.3.

Module V – Dissemination and communication of the results of the preceding modules. This module generates and provides access to 72-hour forecasts, which are updated daily via a web platform and include all results from the previous modules. The Web platform offers a number of functionalities, including. alert maps that identify potentially at-risk elements/activities. Furthermore, Module IV is responsible for issuing two daily bulletins (one pertaining to overtopping and the other to moored ships) to relevant authorities. These bulletins provide details of alerts for the following 72 hours. Furthermore, the bulletins facilitate the continuous validation of the alert system through the feedback received from local authorities, with whom the development team has established cooperative protocols.

3 FORCINGS

3.1 Wind and Wave Forecasts

The system employs a suite of numerical models that utilise forecasts of regional wind and sea-wave characteristics offshore, in conjunction with astronomical tide. A 3-day advance forecast for offshore sea-waves and winds is downloaded (every day) from the High-Resolution Forecasts (HRES) provided by the ECMWF, which currently offers a horizontal resolution of 9 km. The HRES provides detailed descriptions of future weather conditions, available for 3.5 days at 06UTC and 18UTC. The HRES is integrated with the Wave model (ECWAM, which is the ECMWF WAM model, WAMDI, 1988) and the Dynamic Ocean model (NEMO), influencing the development of Tropical Storms. The WAM model is capable of providing accurate forecasts of sea waves parameters, including significant height (Hs), mean and peak periods (Tm and Tp, respectively), and average direction (θm) as illustrated in Figure 4. The spatial resolution of the wave and wind fields is 0.1 degrees. The XTide tool (Flater, 1998) is employed to generate astronomical tide levels, utilising the US National Ocean Service algorithm for tide prediction.

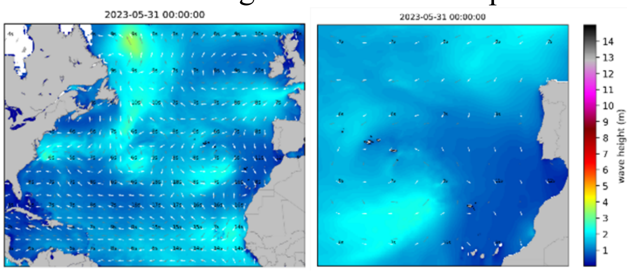

Figure 4. Wave and wind forecasts. ECMWF-WAM & CMEMS Copernicus Marine Service Forecasts.

3.2 Wave Modelling

The wave propagation modelling incorporates three numerical models designed for large scale (SWAN model), and local scale (DREAMS and BOUSSWMH models) analyses, which are supplemented by a finite element mesh generator.

The numerical simulations are conducted on the Central Node for Grid Computing (NCG) of the Portuguese Infrastructure for Distributed Computing (INCD), which comprises a 64-node high-performance computing facility.

The primary model employed is a spectral wind-wave model, which has been designated as a third-generation model and is specifically the SWAN model (Booij *et al.*, 1996). The model is employed over a regional expanse of several hundred kilometres around the test site with three nested computational grids. The model is tasked with solving spectral wave energy (E) balance equation (eq.1) which accounts for energy gained (P – due to wind stress) and energy loss (D – due to wave breaking and friction; R – due to radiation; C – due to wave-current interaction):

$$\frac{\partial E}{\partial t} = P - D - R - C \qquad (1)$$

where E is the wave energy per unit area.

In this context, the SWAN model is employed to simulate the propagation of irregular wave spectrums at the domain boundaries and to convey wave characteristics from the offshore area to the harbour entrance. It is therefore evident that the accurate bathymetric data with high spatial resolution are essential for the SWAN model to be able to effectively shape the complex nearshore processes. The SWAN calculation domains discussed herein were discretized into three nested grids with varying resolutions to address this requirement (Figure 5). At each grid point, the sea state is modelled on the assumption that the integrated spectral variables are representative of a specific area. The wave parameters used to characterize the spectrum are Hs, Tp, and θm. Although this approach is applicable to the west coast of mainland Portugal (Saulnier *et al.*, 2011), on the south coast, the spectrum frequently exhibits a bi-modal distribution, thus necessitating a previous evaluation. In the Azores, the integrated spectral variables are also being considered, although no study has yet been conducted to assess this aspect comprehensively.

The model operates in stationary mode, encompassing a number of key physical processes, including refraction, diffraction, and swell resulting from bottom variations. It also considers wave amplification due to wind, wave breaking influenced by the seabed, white capping, and energy dissipation as a result of bottom friction.

SWAN diffraction computation has limitations, and its formulation is based on an approximate approach. Consequently, to convey wave characteristics from the harbour entrance area to the interior of the harbour, the EWS uses the DREAMS model (Fortes, 2002).

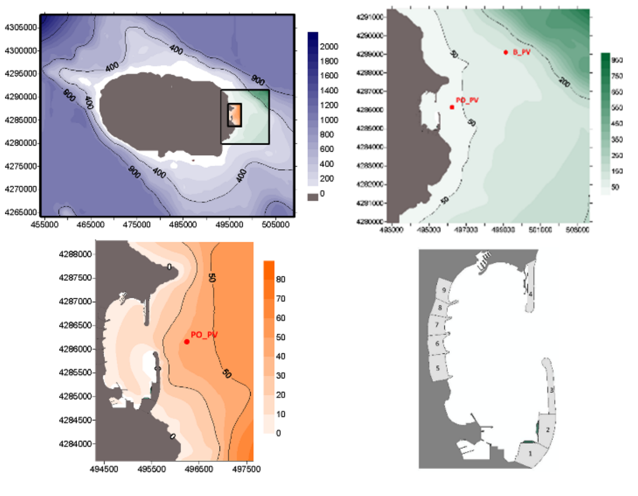

Figure 5. Bathymetry and coarse, medium, and fine grids nested domains for SWAN numerical models. Geographical Location of wave buoys (B_PV and PO_PV).

The models employed for the assessment of wave disturbances inside ports are the DREAMS and BOUSSWMH models. The DREAMS model outputs the sea state characteristics at any point within the port, which are essential to solve the problem of characterizing the motions of a moored ship, Figure 6.

The bathymetry of the study area, used in the simulations with SWAN and DREAMS models, was constructed from hydrographic surveys provided by the Port of Azores Authority.

3.3 Moored Ships

The response of ships to wave and wind forces is computed using SWAMS – Simulation of Wave Action on Moored Ships (Santos, 1994, Pinheiro *et al.*, 2013) numerical modelling tool. This tool incorporates a hydrodynamic 3D panel method model, WAMIT (Korsemeyer *et al.*, 1988), and a motion equation solver, BAS (Mynett *et al.*, 1985). The system assembles and solves the equations of moored ship motion in the time domain, taking into account the time series of forces due to sea waves acting on the ship and the constitutive relations of the mooring system elements.

The prototype system for the Praia da Vitória harbour includes the multipurpose terminal, quay 12, and the container terminal, quay 10. Two ships are modelled, i.e., a general cargo ship and a container ship, respectively, Figure 6. The mooring arrangement of each ship, comprising 10 mooring lines and 5 defences, is depicted in Figure 6,.

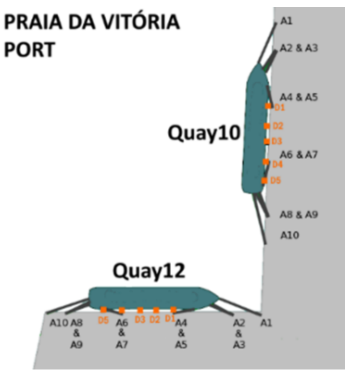

Figure 6. Quay 10 and 12 mooring arrangements for the ships.

3.4 Risk assessment. Moored Ships

Forecasted hourly movements and mooring forces are compared against pre-set thresholds.

The probability assessment of exceedance of these values leads to a risk level assessment. The risk levels are determined based on the Maximum Breaking Load (MBL) of the mooring lines (OCIMF, 1992) and movements (PIANC, 1995, PIANC, 2012).

Based on these risk levels, the system issues alerts, defining danger levels associated with the difficulty of loading and unloading operations and the probability of a component of the mooring system breaking due to excessive ship motions:

- No danger (level 0 - green symbol): No changes are required in port activities.
- Low danger (level 1 - yellow symbol): Loading and unloading operations are subject to certain conditions. It is possible to reinforce mooring lines.
- Moderate danger (level 2 - orange symbol): Loading and unloading operations are not possible. It is necessary to reinforce the mooring lines.
- Maximum danger (level 3 – red symbol): Loading and unloading operations are suspended. There is a possibility of breakage of mooring system elements and structural damage.

The risk levels pertaining to the ships' motions and the forces on their mooring lines are colour-coded and symbolized in order to facilitate the issuance of system alerts.

4 FORECAST OPTIMIZATION

4.1 Forecast validation

Initially, wave and wind climates were established to characterize the met-ocean conditions of the region. Four points were selected for extracting wave and wind forecasts from the global Atlantic Ocean meteorological model, Figure 7, which is provided by the European Centre for Medium-Range Weather Forecasts, ECMWF (Persson, 2001).

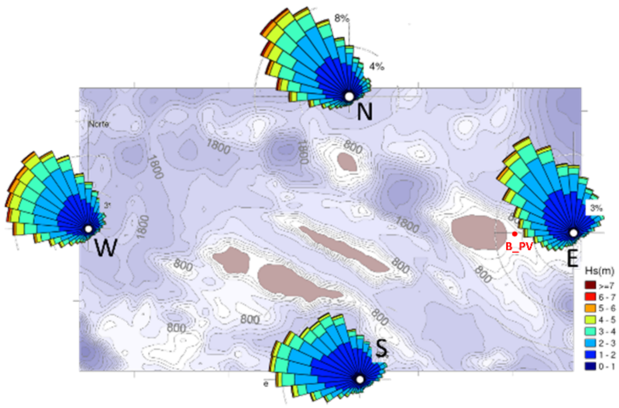

Figure 7. HIDRALERTA EWS four points (N, S, E, W) of offshore wave/wind data used for long-term analysis and as forecast forcing data.

Figure 8 presents statistical data for the representative offshore wave and wind regime (point W, Figure 7) alongside buoy measurements of wave height statistics (point B_PV, Figure 5), covering the data period from 2005 to 2020. The offshore wave regime is characterized by waves predominantly originating from the NW quadrant, accounting for over 80% of the records, while the wind regime is primarily from the SW quadrant. At the buoy (B_PV, Figure 5) location the wave regime has undergone a shift due to the diffraction effect around Terceira Island, resulting in a more predominant direction from N.

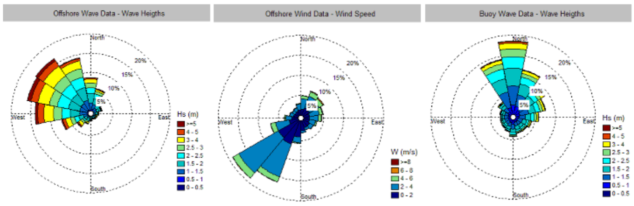

Figure 8 - Offshore (point W) wave (left) and wind (centre) statistics provided by ECMWF. Buoy (B_PV) measurements wave statistics (right). The dataset encompasses the period from 2005 to 2020.

A comprehensive long-term error analysis was conducted using a 15-year dataset (wave and wind data) from the ERA5 reanalysis model of the ECMWF, which employs the WAM model (WAMDI Group, 1988). The aforementioned dataset serves as the input for the boundary conditions in SWAN simulations, as implemented in the EWS.

The Root Mean Square Errors (RMSE) for the significant wave height, Hs, at the buoy location were recorded at 0.61m (indicating an overestimation by SWAN compared to buoy measurements) and 2.36s for the mean period, Tz (which also reflects an overestimation).

The monitoring of wave characteristics is of paramount importance for the validation of the results generated by numerical models, on a daily basis, the discrepancies between the forecasts and wave characteristics are assessed daily, Figure 9.

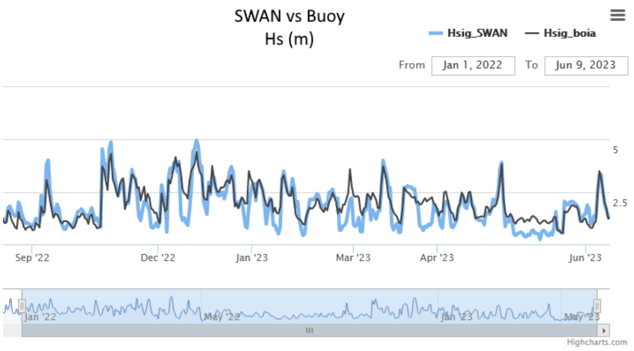

Figure 9. HIDRALERTA EWS validation of wave parameters against wave buoy measurements.

The outcomes of continuous validation of the wave characteristic forecasts at the buoy location indicated that the development of neural networks would enhance these forecasts.

4.2 Neural Networks

4.2.1 *Model training*

A machine learning (ML) model was developed to analyse and predict ocean wave characteristics using data collected from wave buoys, Figure 10. The ML developed for the Port of Praia da Vitória was based on the methodology previously applied to the port of Sines (Pinheiro *et al.*, 2022). Three Neural Networks were designed and trained (one for each wave parameter at the buoy, Hs, Tz, and θ) to explore the potential for enhancing the accuracy of the forecasts. The development of the NNs was conducted utilising Kera, an open-source neural network library written in Python. The input data for the NN comprised a combination of wave heights, periods and directions, along with wind velocity and direction (Brownlee, 2019).

The NN were trained using the 15-year dataset mentioned above (section 4.1). The dataset enabled the NN to identify patterns within the data and make accurate predictions about future wave conditions based on current environmental conditions. The training process was designed to minimize the discrepancy between the predicted outputs and the actual measurements (Loss or RMSE in this case). The dataset was divided into two distinct sets, with 80% allocated for the training of the network and 20% reserved for testing. The cost function employed was the mean squared error, MSE, of the entire training set. The rectified linear unit (ReLU) activation function was employed to introduce non-linearity into the network.

Each neural network (NN) in the machine-learning model incorporated five input layers corresponding to offshore wave parameters (Hs, Tz, and θ) and wind data (velocity and θ). The input nodes comprised the offshore wind and sea-wave data provided by ECMWF over a 15-year period, including significant height (Hs), the mean period (Tz), the average direction (θm) of the sea waves, and wind velocity and direction, covering the period between 2005 and 2020, Figure 8.

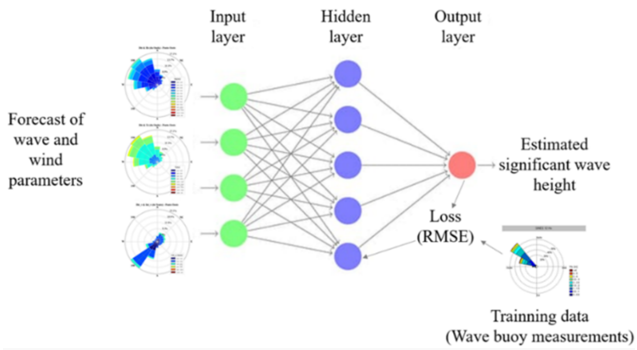

Figure 10 – Structure of the Neural Network for the wave height estimation/forecast at the B_PV Buoy.

The parameters that can influence the network's accuracy in reflecting reality include the number of neurons, the batch size (bs), and the number of epochs. The batch size refers to the number of training examples used in one forward/backward pass. A larger batch size necessitates the use of more memory. The number of epochs indicates the number of times that the model is exposed to the training dataset.

The optimal parameters for configuring the neural network were selected in three stages. In stage 1, the number of neurons (32, 64, 128) and the number of epochs (800, 1000, 2000) were varied while maintaining a fixed batch size of 1024 values. This established the optimal settings for stage 2, namely the number of neurons and the number of epochs. In stage 2, the batch size was varied while using the optimal neuron and epoch values identified in stage 1. Stage 3 involved a new iteration of the first stage, employing the optimal batch size determined in the second stage. The most effective configurations were identified as follows: for the Hs NN - batch size=153, neurons=32, epochs=2000; for the Tz NN - batch size=200, neurons=32, epochs=1000, Figure 11.

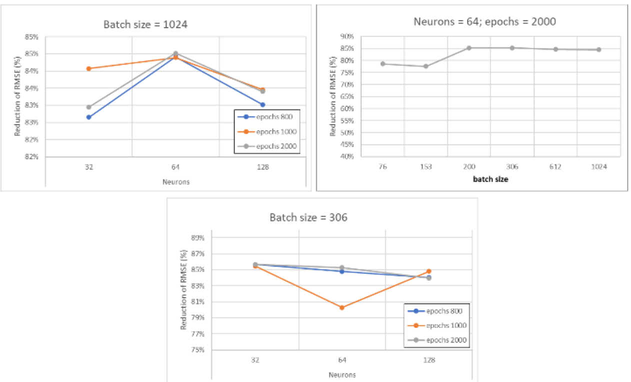

Figure 11 – Three stages of NN, wave height (Hs) parameters optimization.

4.2.2 *Real-time prediction and forecasting optimization*

Once the NNs have been trained and optimized, the machine learning model is integrated into the operational wave forecast models and utilised to make real-time predictions about ocean wave conditions at the buoy location, based on the forecasts supplied daily by weather and marine forecast providers (ECMWF and the Copernicus Marine service).

Upon comprehensive analysis of the entire dataset, Figure 12, the NN estimations are compelled to align with the measured data. This adjustment is most evident in the Tz parameter, which is significantly overestimated by the SWAN model. It is crucial to recognise that the SWAN model does not accurately replicate the wave period. This limitation is due to the formula used in its spectral method, which relies on the zero and second-order moments of the spectrum and thus considers all waves present in the record, including the smallest ones (Capitão &Fortes, 2011).

It is also evident that Hs is consistently overestimated by the outputs of the SWAN model. In this process, while the majority of predictions produced by the NNs demonstrate an improvement, a subset does not. For instance, the scattered orange points below the 1:1 line in Figure 12 illustrate deviations from the ideal predictions.

An analysis of the test data (which comprises data not included in the training data and thus represents how the system will likely perform in future forecasts) reveals that while the SWAN model tends to overestimate predictions, the NN predictions more closely align with the optimal 1:1 line for the Hs parameter (Figure 13).

Figure 14 presents frequency histograms comparing buoy measurements, NN outputs, and SWAN numerical simulations. It demonstrates that the NN model produces a more accurate adjustment in terms of distribution frequency over the data ranges of Hs.

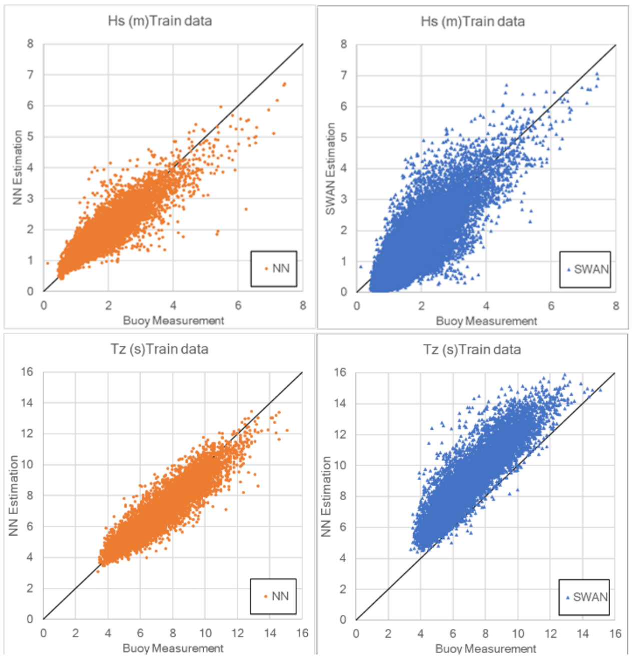

Figure 12 – Significant wave height. Comparison of the NN and SWAN train data. Left: NN; Right: SWAN.

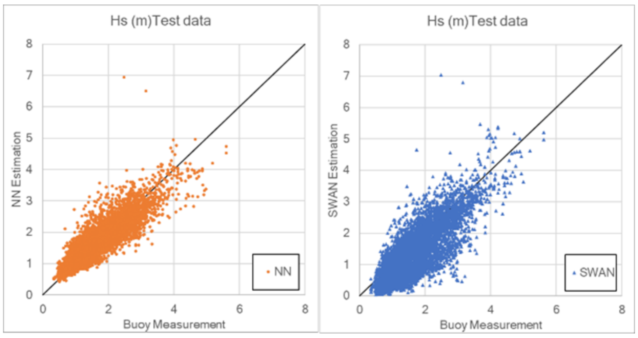

Figure 13 – Significant wave height. Comparison of the NN and SWAN test data. Left: NN; Right: SWAN.

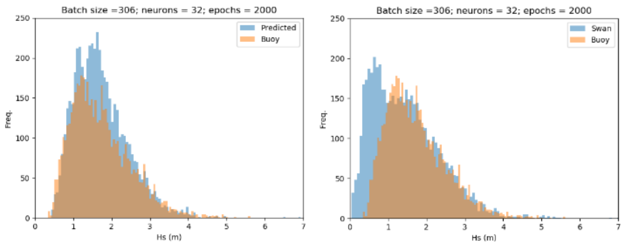

Figure 14 – Comparison of the frequency histograms of Significant wave height Buoy measurements, Neural Network output, and SWAN numerical simulations.

Upon examining the last 400 records of the buoy measurements and comparison with the outputs from the NN and SWAN models, Figure 15, it is evident that the NN has made significant improvements, particularly at the peaks, which are the critical moments for this kind of EWS.

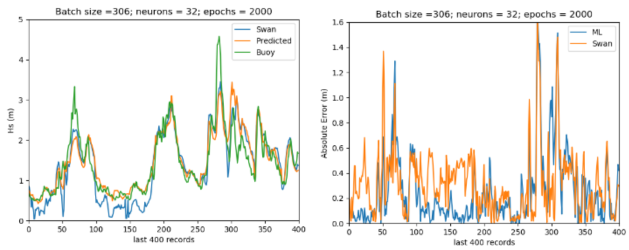

Figure 15 – Comparison of the last 400 records of the Significant wave height Buoy measurements, Neural Network output, and SWAN numerical simulations.

Table 1 presents the overall mean absolute error (MAE) and root mean square error (RMSE) for the SWAN numerical model and the NN. The error reduction is notable. The application of the aforementioned neural network (NN) resulted in an 80% reduction of the RMSE of significant wave height and a 78% reduction for the mean wave period, in comparison to the SWAN model simulations.

Table 1 – Mean absolute error and root mean square error for SWAN numerical model and NN.

	batch size	neur	epoc	MAE (m)		RMSE (m)	
				SWAN	NN	SWAN	NN
Hs	306	32	2000	0.47	0.26	0.61	0.12
Tz	1024	64	800	2.13	0.54	2.36	0.52

The RMSE for the Hs decreased from 0.61m to 0.12m. In comparison, other calibration methods, such as nonlinear regression, which have been used to calibrate significant wave height time series using both buoy measured data and satellite data (Mínguez et al. 2011), were able to reduce the Hs RMSE from 0.59 to 0.43.

The clear evidence that the developed NN produces more accurate predictions of Hs and Tz at the buoy location led to the integration of these networks into the warning system architecture. Consequently, the results for the entire domain of the 3rd SWAN nested grid are now adjusted using a simple correction factor, which is determined by the percentage difference between the NN and SWAN computed parameters. It is anticipated that this adjustment will enhance the accuracy of subsequent calculations performed by the EWS, including wave propagation into the port domain and the assessment of forces and motions of the ships.

Moreover, these NN algorithms can be continuously updated with new data to improve their performance over time.

5 DISSEMINATION AND COMMUNICATION

Based on the results obtained, various layouts are produced by HIDRALERTA. All information generated by this EWS is accessible via a dedicated website (http://aurora.lnec.pt) and mobile application. Currently, access to both platforms is restricted to authorized users (Figure 16), as certain details concerning port infrastructures are confidential. Furthermore, an alert bulletin is disseminated to stakeholders via email. Therefore, port stakeholders are equipped with a decision-support tool that enables them to implement mitigation measures in a timely manner, thereby preventing accidents and minimising economic losses.

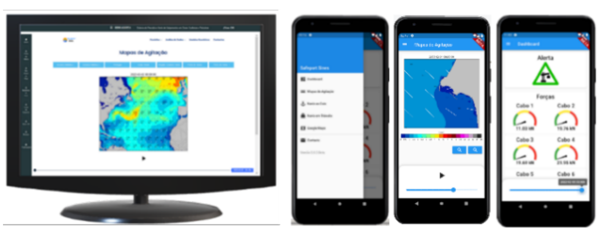

Figure 16. HIDRALERTA EWS web page and mobile application.

Figure 17 shows the dashboard of alerts disseminated on the SAFEPORT system platforms.

Figure 17. Dashboard of the alerts for the forces on the ships' mooring lines.

6 CONCLUSIONS

The EWS utilises offshore forecasts generated by precise weather-oceanographic forecasting models to calculate relevant wave parameters for the assessment of the behaviour of ships moored within port basins. This is achieved through the use of a suite of numerical models. The EWS issues alerts corresponding to danger levels associated with the ships' motions and forces exerted on their mooring lines. The results are disseminated via digital platforms, specifically a web page and a mobile application.

The effectiveness of this EWS is contingent upon the accuracy of the atmospheric and wave forecasts, as well as the numerical models used for wave propagation and the behaviour of the moored ships. Consequently, the system's reliability is contingent upon the potential for errors to arise from the models' parameterisation and approximations, as well as from the boundary conditions imposed upon these models.

This paper presents a novel approach to numerical wave prediction models that employs neural networks to mitigate errors and enhance efficiency.

Such machine learning (ML) algorithms are capable of learning from historical data and identifying patterns that might elude human experts, thus fostering more accurate and reliable forecasts.

The neural networks trained in this study have demonstrated their capacity to generate more accurate estimates for the significant wave height and mean wave period at the buoy location situated in front of the Port. The use of the newly developed NNs has resulted in a substantial reduction of the RMSE, with a reduction of approximately 80% compared to simulations from the SWAN numerical model. Consequently, this facilitates a more accurate determination of wave characteristics in front of the port, which, in turn, allows for a more precise estimation of the mooring forces on ships and the wave overtopping risks. The integration of these NN significantly enhances the accuracy and reliability of the EWS.

Moreover, NN algorithms are capable of adapting to changes in environmental conditions, such as climate change or alterations in the coastline. This adaptability ensures the continued effectiveness of the EWS over time.

However, it is important to note that NN algorithms may exhibit overfitting of the training data, which may result in a lack of generalisation to new data sets. This proclivity can result in erroneous predictions when applied to real-world scenarios. Consequently, it is imperative to exercise caution when conditions alter, in order to ensure the reliability of the predictions. The application of machine learning is a powerful tool with the potential to enhance the accuracy and reliability of EWS. As ML techniques continue to evolve, they are poised to play an increasingly critical role in safeguarding coastal communities from the devastating effects of coastal hazards.

An effective EWS, when integrated with soft adaptation measures, can significantly enhance the protection of people, property, and environmental assets.

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