NEURAL NETWORKS FOR OPTIMIZATION OF AN EARLY WARNING SYSTEM FOR MOORED SHIPS IN HARBOURS

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Within the BlueSafePort project, an early warning system (EWS) for moored ships in the port of Sines was developed. In order to improve the reliability and accuracy of the system, two neural networks (NN) were trained, using wave buoys measured datasets. Numerical models results for the wave propagation are adjusted and forecasts are improved. The trained neural networks were able to produce more accurate estimates for the significant wave height and mean wave period, at the buoy location, deployed in front of the Sines Port. The use of the new NN led to an overall reduction of the root mean square error of around 80% compared with SWAN numerical model simulations, thus reducing potential errors in subsequential calculations and alert levels issued by the system for the moored ships.

INTRODUCTION

World trade by sea has been growing at an increasing rate and is expected to continue to do so in the near future. At the crossroads of the world's main maritime routes, some of the main commercial Portuguese ports have a favorable geographical position in the Atlantic Ocean, as well as infrastructure capacity to grow with the ever-increasing demand. Given the importance of its ports, it is not viable for their port terminals the operation to experience unwanted downtime, which can lead to major economic losses and greatly affect the overall competitiveness of the ports. An efficient port operation is directly related to the weather-oceanographic conditions to which they are exposed. The occurrence of storms and other met-ocean phenomena can result in damage to port structures and ships (maneuvering or mooring) and for port operational problems. Port safety and operability is also directly related to keeping ship movements within established limits, both during maneuvers entering/exiting the port, during berthing maneuvers and while the ships are moored.

Within the BlueSafePort project, an Early Warning System (EWS), SAFEPORT-Sines, was developed for forecasting and alerting for potential hazards in the port of Sines, namely ship moorings failure and operational constraints. The goal of such EWS is to reduce the port's vulnerability by increasing its planning capacity and efficient response to emergency situations. As any EWS, its usefulness depends greatly on its reliability and accuracy so it is essential that the system operates properly both in normal and stormy situations.

The EWS uses numerical models which provide a good means to detect adverse events. Despite advances in the sophistication of such models, these are still in need of improvement and calibration to achieve more accurate and reliable results.

To achieve more accurate predictions a new machine learning method was developed to optimize forecasts produced by the system. Using available database from buoys, pressure sensors and meteorological stations, neural networks can be trained to optimize numerical models results. The employed method is based on Neural Network (NN) modeling of wave propagation, using a point-based measured data that can be used to correct wave spectral parameters in the whole numerical propagation domain.

TEST CASE – PORT OF SINES

The Port of Sines is a deep-water port located on the west coast of mainland Portugal. The port has 7 terminals, namely: the Liquid Bulk Terminal (TGL), the Liquified Natural Gas Terminal (TGN), the Petrochemical Terminal (TPQ), the Sines Container Terminal or Terminal XXI (TCS), the Sines Multipurpose Terminal (TMS), the Fishing Port and the Sines Marina.

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Figure 1. Port of Sines test case.

In the harbor basin protected by the eastern breakwater are frequent reports of significant agitation that induces excessive movements in ships moored at TXXI. There are also frequent reports of excessive movements while observing an apparently calm state of sea agitation.

Thus, a prototype of the SAFEPORT-Sines has been developed and validated for the Port of Sines, focusing on the risks related to excessive movements of an oil tanker at the TGL, a general cargo ship at the TMS, and a container ship at the TCS (Figure 1). Table 1 and Figure 2 presents general geometric characteristics of the simulated ships as well as the mooring arrangements that are part of the EWS implemented and in operation.

The TGL is harbored by the western breakwater of the Port of Sines and has natural depths of up to 28 meters ZH, with capacity to receive ships up to 350,000 tons dwt. The TMS and TXXI are harbored by the eastern breakwater of the Port of Sines. The TMS has natural depths of up to 18 meters ZH and capacity to receive ships up to 190,000 tons dwt. The TXXI, in turn, has natural depths of up to 17 meters ZH and in 2020 received the largest container ship in the world which has a capacity of 23,756 TEU.

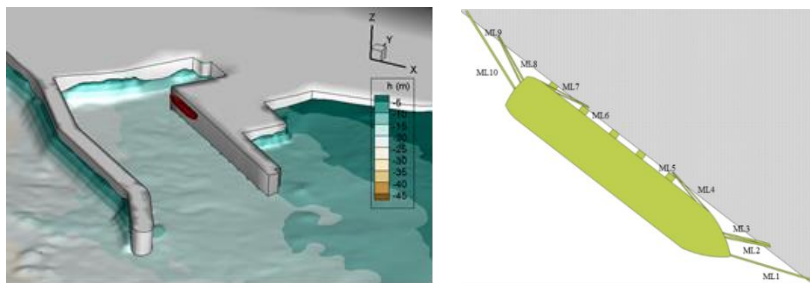| Table 1 - General geometric characteristics of the simulated ships.				
Ship	Draft (m)	Beam (m)	Lenght Overall (m)	Moorings
Oil Tanker	22.0	26.5	340	8ML + 3FD
General Cargo	10.5	30.0	220	8ML + 5FD
Container Ship	8.0	19.0	120	10ML + 6FD

Figure 2 - Terminal XXI bathymetry. 3D view of the basin and ship's location. Mooring lines and fenders arrangements of the container ship.

EARLY WARNING SYSTEM

The SAFEPORT-Sines EWS follows a series of EWS from the HIDRALERTA platform which includes three Azorean ports: Praia da Vitória, São Roque do Pico and Madalena do Pico, (Poseiro, 2019 & Pinheiro et al., 2020), and six other ports in mainland: Ericeira (To-SEAlert project), Costa da Caparica (To-SEAlert project), Sines (BLUESAFEPORT project), Peniche (BSafe4Sea project), Faro and Quarteira.

As any complete and effective EWS, the HIDRALERTA architecture, Figure 3, was developed based on the four inter-related elements of an EWS: risk knowledge, monitoring and warning service, communication and dissemination, and response capabilities (Basher, 2006 & ISDR Plataform).
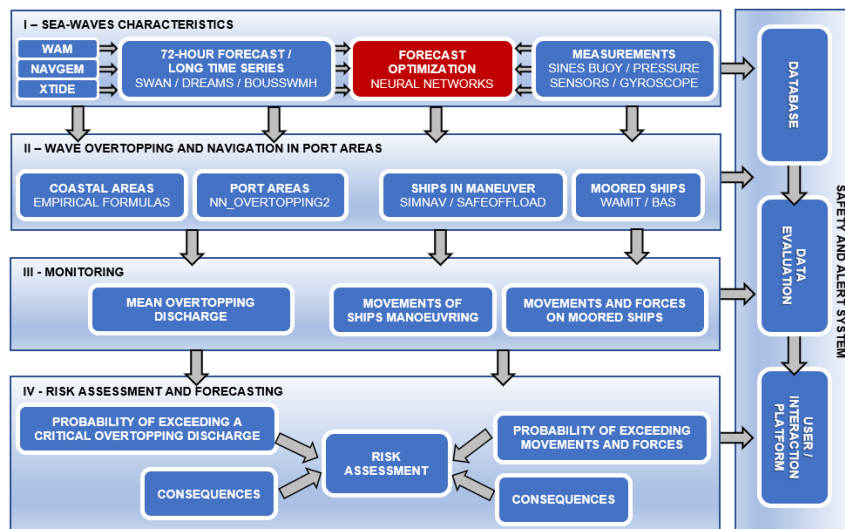
Figure 3. SAFEPORT-Sines EWS architecture with NN modelling.

Wind and Wave Forecasts

The system uses available forecasts of regional wind and sea-wave characteristics offshore, together with astronomical tidal data as inputs to a set of numerical models. The 3-day advance offshore sea-wave forecast is downloaded (every day) through the European Centre for Medium-Range Weather Forecasts (ECMWF) (Persson, 2001), which uses the WAM model (WAMDI Group, 1988). WAM enables accurate forecasts in terms of the sea waves significant height (Hs), mean and peak periods (Tm and Tp, respectively) and average direction (θm). The wind fields forecasts are produced by the NAVGEM model, executed by the US Navy's high-resolution global weather forecast system at the Fleet Numerical Meteorology and Oceanography Center (Whitcomb, 2012). Sea levels of astronomical tide are produced with the XTide tool (Flater, 1998) which uses the same algorithm used by the National Ocean Service in the US to predict tide.

Wave Modelling

The wave propagation modelling includes two numerical models for wave propagation on large scale and on local scale and a finite element mesh generator.

The first model is a spectral wind-wave models, known as third-generation models, SWAN model (Booij et al., 1999), used on a region of a couple hundred kilometers covering the test site with three nested computational grids. This model solves the spectral wave energy (E) balance equation with 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 framework, SWAN model is used to simulate the propagation of irregular wave spectrums on the domain boundaries and to transfer the wave characteristics from the offshore area to the harbor entrance. SWAN requires bathymetric data with high spatial resolution to model the complex nearshore processes. The SWAN calculation domains presented here, were discretized into three nested grids with different resolutions to address this issue (Figure 4). The sea state is modelled at each grid point assuming that the empirical JONSWAP spectrum represents the real spectrum of waves approaching the port. The wave parameters used to characterize the spectrum are Hs, Tp, and θm.

The model runs in stationary mode considering the physical processes of refraction, diffraction and swell due to bottom variations, wave growth by wind action, wave breaking by bottom influence and whitecapping and energy dissipation due to bottom friction.

SWAN diffraction computation has limitations, and its formulation is based on an approximate approach. Thus, to transfer the wave characteristics from the harbor entrance area to the harbor's interior the EWS uses DREAMS.
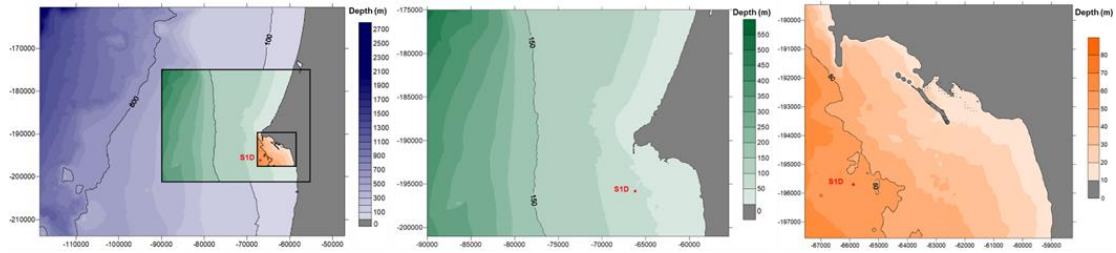
Figure 4. Bathymetry and coarse, medium and fine grids nested domains for SWAN numerical models. Geographical Location of wave buoy (S1D).

The numerical model DREAMS (Fortes, 2002) is a linear finite element model, based on the mild slope equation, to simulate the propagation of monochromatic waves.

$$\nabla \cdot \left(c_P c_g \nabla \eta\right) + k^2 c_P c_g \eta = 0 \qquad (2)$$

Where η is the complex-valued amplitude of the free-surface elevation $\zeta(x, y, t)$; (x, y) is the horizontal position; ω is the angular frequency of the monochromatic wave motion; k is the wavenumber; c_P, is the phase speed of the waves and c_g, is the group speed of the waves.

DREAMS model is fully implemented in the EWS. It also requires the definition of a calculation domain, characterized by a boundary and a bathymetry of the port region. The calculation domain is discretized through a non-structured mesh of triangular finite elements built with the GMALHA automatic generator (Pinheiro et al., 2008). A finite element mesh is generated based on a criterion of a density of nodes per wavelength and to the minimum period of the wave. The mesh topology was optimized so that the most equilateral triangles would be possible, and the nodal numbering was reordered to optimize the bandwidth required for the numerical model. All this improves the results quality and reduces the computational cost of the numerical simulations.

The bathymetry of the study area used in the calculations with numerical models was built from hydrographic surveys provided by the Port of Sines Authority.

DREAMS model boundary conditions consist of the generation-radiation conditions at the open boundaries, the total or partial reflection conditions of the solid boundaries of the portss, i.e. beaches, slopes, ramps, vertical walls and breakwaters, and wave data provided by SWAN and imposed at a transfer point located in front of the ports. Finally, DREAMS results consist of the sea state characteristics at any point located within the port, required to solve the problem of characterizing the motions of a moored ship, Figure 5.
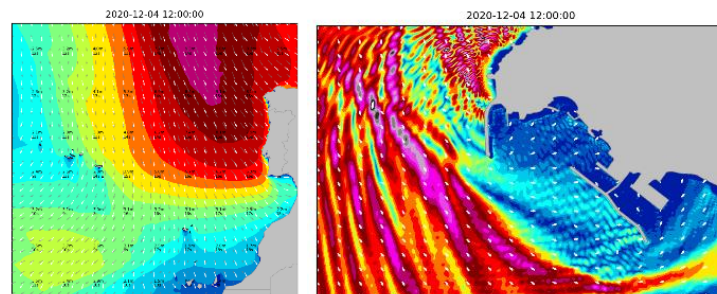

Figure 5 - Wave and wind forecasts. ECMWF-WAM forecasts (right). DREAMS model results (left)

Moored Ships

Finally, the ship's response to those wave and wind forcings is computed using SWAMS - Simulation of Wave Action on Moored Ships (Pinheiro et al. 2013) numerical modelling tool which includes a hydrodynamic 3D panel method model WAMIT (Korsemeyer et al. 1988) and a motion equation solver, BAS (Mynett *et al.* 1985) that assembles and solves, in the time domain, the equations of moored ship motion 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 moored ship movements and the forces exerted on the mooring system, in its 6 degrees of freedom are outputs.

The equation of motion for the moored ship is as follows:

$$\sum_{j=1}^{6}\left[(M_{kj}+m_{kj})\ddot{x}_j(t)+\int_{-\infty}^{t}K_{kj}(t-\tau)\,\dot{x}(\tau)\,d\tau+C_{kj}x_j(t)\right]=F_k^d(t)+F_k^m(t)+F_k^f(t) \tag{3}$$

where M_{kj} is the mass matrix of the ship and C_{kj} is the hydrostatic restoring matrix whose coefficients are the force along mode k due to a unit change, in still water, of the ship position along mode j. F_k^d is the force along each degree of freedom k that is exerted by the incident sea waves on the ship's hull. $F_k^m(t)$ and $F_k^f(t)$ are the instantaneous values of the forces due to mooring lines and fenders.

Strictly speaking, this is a set of six equations whose solutions are the time series of the ship movements along each of her six degrees of freedom as well as of the efforts in the mooring lines and fenders. In the equation above mass and hydrostatic restoring matrices depend only on the ship geometry and on the mass distribution therein. The forces due to mooring lines and the fenders can be determined from the constitutive relations of these elements of the mooring system.

Numerical models are coupled through a python script routine and simulations run on the Central Node for Grid Computing (NCG) of the Portuguese Infrastructure for Distributed Computing (INCD), a 64-node high performance computing facility.

Forecasted hourly movements and mooring forces are compared with pre-set thresholds. Probability assessment of exceedance of those values results in a risk level assessment. Risk levels depend on the Maximum Breaking Load (MBL) of the mooring lines (OCIMF, 1992) and movements (PIANC 1995; PIANC 2012;).

Based on the risk levels, the system issue alerts, through the definition of danger levels related to the difficulty of loading and unloading operations and the probability of breakage of an element of the mooring system, due to excessive ship motions:

- No danger (level 0 - green symbol): No changes in port activities.
- Low danger (level 1 - yellow symbol): Loading and unloading operations conditioned. Possibility of mooring lines reinforcement
- Moderate danger (level 2 - orange symbol): Loading and unloading operations cannot be performed. Required reinforcement of mooring lines.
- Maximum danger (level 3 - red symbol): Loading and unloading operations are suspended. Possibility of breakage of mooring system elements and structural damage.

The risk levels, relating to the ships' motions and the forces on their mooring lines, have been color-coded and symbolized to issue the SAFEPORT system alerts.

Figure 6 shows the dashboard of alerts disseminated on the SAFEPORT system platforms.

Figure 6. Dashboard of the alerts for the forces on the ships' mooring lines.

From the results, different layouts are created by SAFEPORT-Sines. All information provided by this EWS is available in a dedicated website and mobile application (Figure 7). Additionally, an alert bulletin is sent by email to interest parties. Thus, port stakeholders benefit from a decision- support tool

to timely implement mitigation measures and prevent accidents and economic losses. Numerical simulations run on the Central Node for Grid Computing (NCG) of the Portuguese Infrastructure for Distributed Computing (INCD), a 64-node high performance computing facility.
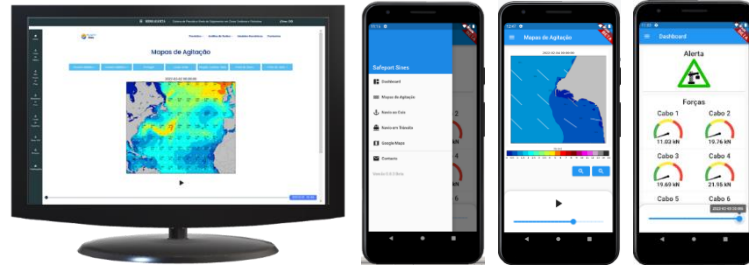

Figure 7. SAFEPORT-Sines EWS web page and mobile application.

MACHINE LEARNING MODEL

In situ monitoring of wave characteristics are used to validate the results produced by the numerical models, and the deviations between forecasts and wave measurements are assessed daily. Additionally, a long-term error analysis was performed using a 40-year dataset (wave and wind data) from the ERA5 reanalysis model of the European Centre for Medium-Range Weather Forecasts, ECMWF (Persson, 2001), that uses WAM model (WAMDI Group, 1988), to initiate SWAN simulations exactly as they are implemented on the EWS. The Root Mean Square Errors (RMSE) for significant wave height, Hs, at the buoy location, is 0.395m (with SWAN's overestimating buoy measurements) and 2.36s for the mean period, Tz (also overestimation).

A machine learning model was designed to analyze and make predictions about ocean wave characteritics using data collected by wave buoys, Figure 9. Three Neural Networks were trained in order to evaluate the possibility of improving these forecasts accurateness. For the development of the NNs, Keras open-source neural network library, written in Python, was used. Each neural network is built using a series of interconnected nodes, also called artificial neurons, that process input data and produce output predictions. The input data for the neural network is a combination of wave heights, periods and directions and wind speed and direction. These inputs are fed into the neural network (input layer), which processes the data through a series of hidden layers before producing output predictions (output layer).

Each layer has a certain number of nodes. All the neurons in a hidden layer are connected to every neuron in the next layer. The Output Layer is the last layer in the network & receives input from the last hidden layer.

The neural network is trained using a dataset of historical wave buoy measurements and associated environmental conditions. This dataset is used to train the neural network to recognize patterns in the data and make accurate predictions about future wave conditions based on current environmental conditions. The training process involves adjusting the weights and biases of the artificial neurons to minimize the difference between the predicted output and the actual output (Loss or RMSE in this case).

Five input layers were used for the development of each NN in the machine learning model. Offshore wave parameters (Hs, Tz and θ) and wind data (speed and θ). Input nodes data consist of the offshore wind and sea-waves 40-years dataset are supplied by ECMWF, significant height (Hs), the mean period (Tz) and the average direction (θm) of the sea waves and wind speed and direction, between 1988 and 2018, Figure 8. Training data consists of an available dataset of measured wave characteristics from the Sines 1D wave buoy which has been deployed since 1988 and all the available data until 2018 wave buoy data was used, Figure 8.
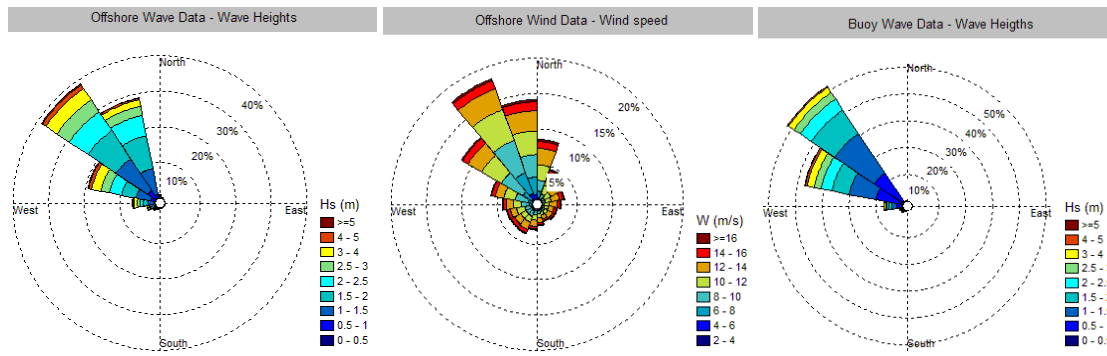
Figure 8 - Offshore wave (left) and wind (center) statistics. Buoy measurements wave statistics (right). Data period from 1988 to 2018.

In this case three different NN were created, one for each wave parameter at the buoy, Hs, Tz and θ, so only one output per NN was required. 80% of the data was used to train the network and 20% was used to test it. The cost function is the mean squared error, mse, of the entire training set. The rectified linear unit (ReLU) activation function is used to introduce non-linearity to the network.
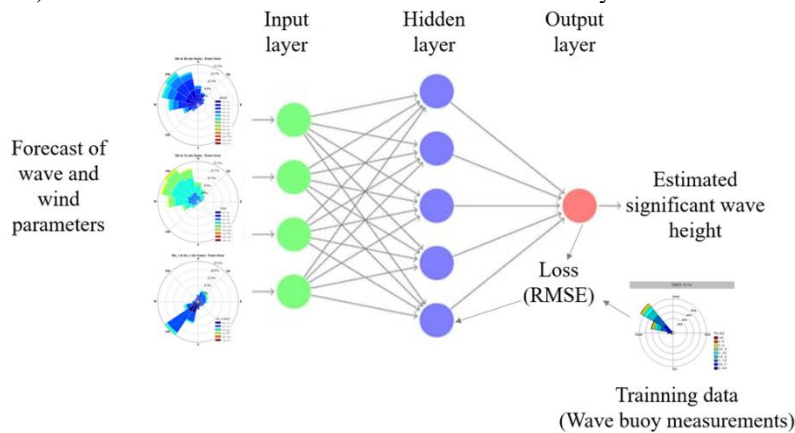

Figure 9 – Structure of the Neural Network for the wave height estimation/forecast at the Sines Buoy.

For the generation of a NN some parameters have to be defined and can influence the fit of the network to reality, namely, the number of neurons, the batch size (bs) and the number of epochs. The batch size is the number of training examples in one forward/backward pass. The higher the batch size, the more memory is needed. The number of epochs is the number of times that the model is exposed to the training dataset.

The selection of the best parameters for the generation of the neural network was performed in 3 stages. The first stage varied the number of neurons (32, 64, 128) and the number of epochs (800, 1000, 2000) while using a fixed batch size of 1024 values. The best score in terms of reduction of the RMSE sets the neurons and epochs for the next stage. The second stage consists of varying the batch size while using fixed values for neurons and epochs. Finally, the third stage is essentially a new run of the first stage with the best batch size obtained in the second stage. The best fit for the Hs NN was achieved with batch size = 153, neurons = 32, epochs = 2000. For the Tz NN, the best fit was achieved with a batch size = 200, neurons = 32, epochs = 1000, Figure 10.

After the neural networks are trained and optimized, the machine learning model is embedded into the forecast wave models train and is used to make real-time predictions about ocean wave conditions at that specific site (buoy location) based on the forecasts of environmental data supplied daily form the weather and marine forecast providers (ECMWF and Copernicus Marine service).
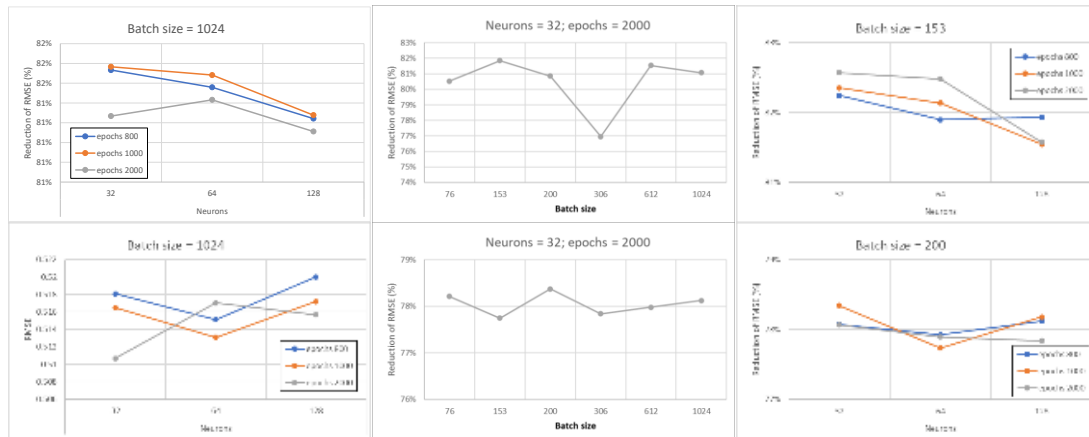
Figure 10 – Three stages of NN parameters optimization. Top: H; Bottom: Tz.

Analyzing the whole set of the training data, Figure 11, it is clear that the NN estimation is forced to adjust to the measured data. That is most clearly seen in the Tz parameter, which is largely overestimated by SWAN model. It should be noted that SWAN does not accurately simulate the wave period, due to the calculation formula used in the spectral method, which, implicitly, through the zero and two order moments of the spectrum, considers all existing waves in the record, even the smallest ones (Capitão and Fortes, 2011).

Hs is also overestimated by SWAN results. In this process, although the vast majority of predictions given by the NN are improved, some are not. For instance, the scattered orange points in the first graph, below the 1:1 line, show that the NN produced some underestimations that in fact SWAN was giving a better estimation.
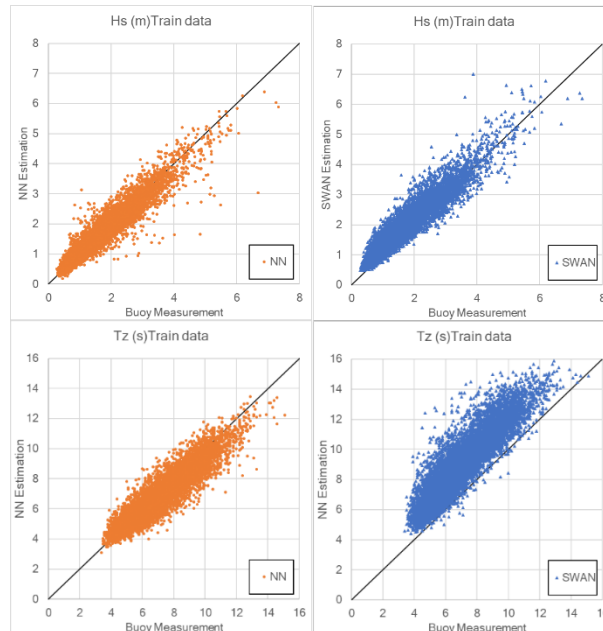

Figure 11 – Comparison of the Neural Network and SWAN train data. Top: Significant wave height; bottom: Mean wave period.

Analyzing the test data, which is the data that was not in the training data set, so it can be said to represent how the system will behave in future forecasts, it can be seen that, for the Hs parameter, SWAN model overestimates predictions while the NN is more centered around the optimal 1:1 line.
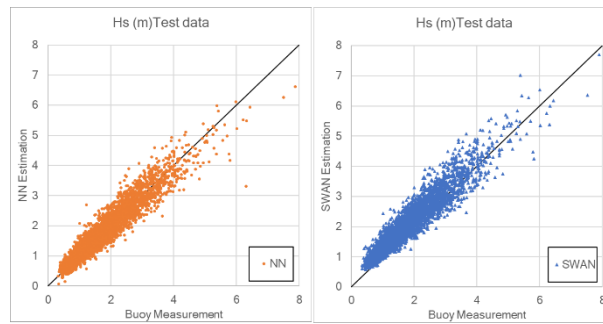
Figure 12 – Comparison of the Neural Network and SWAN test data. Top: Significant wave height; bottom: Mean wave period.
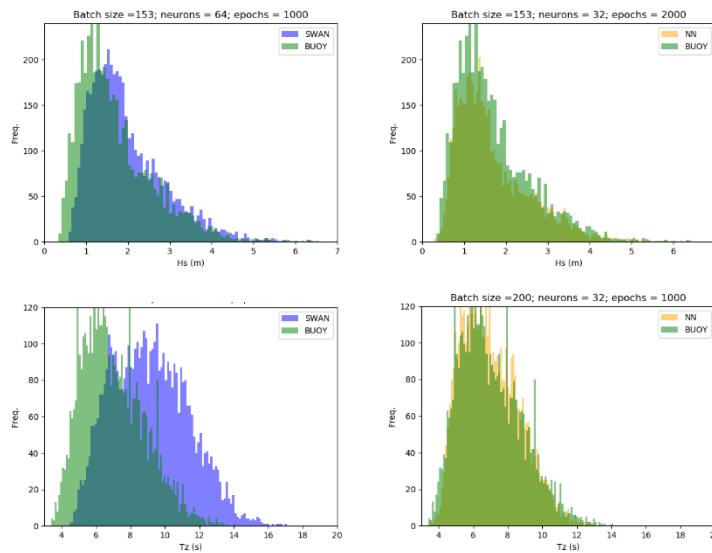

Figure 13 – Comparison of the frequency histograms of Buoy measurements, Neural Network output and SWAN numerical simulations. Top: Significant wave height; bottom: Mean wave period.

In Figure 13, the frequency histograms of Buoy measurements, Neural Network output and SWAN numerical simulations comparison shows a better adjustment in terms of distribution frequency over the data ranges of Hs and Tz.

If we look at the last 100 records of the Sines1D buoy measurements and compared with the NN and SWAN outputs, Figure 14, it can be seen the improvement made by the NN, especially in the peaks, wich are the critical moments for this kind of EWS.
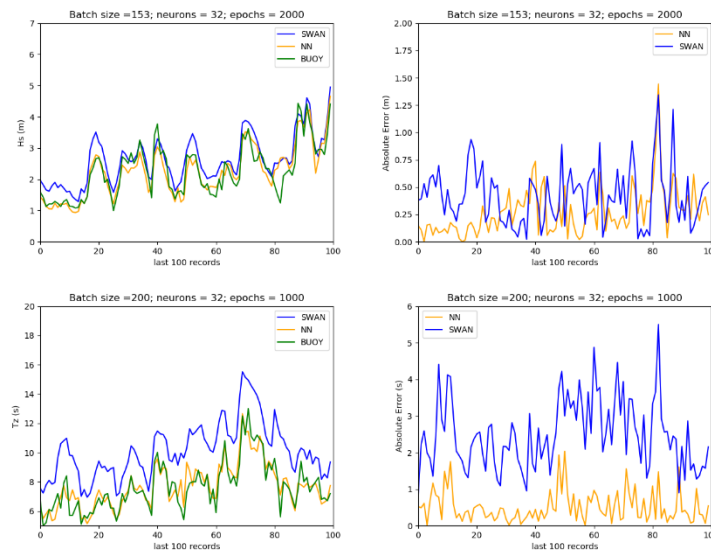
Figure 14 – Comparison of the last 100 records of the Buoy measurements, Neural Network output and SWAN numerical simulations. Top: Significant wave height; bottom: Mean wave period. Right: absolute error.

Table 2 – Mean absolute error and root mean square error for SWAN numerical model and NN.							
	batch size	neurons	epochs	MAE		RMSE	
				SWAN	NN	SWAN	NN
Hs (m)	153	32	2000	0.33	0.19	0.40	0.07
Tz (s)	200	32	1000	2.13	0.54	2.36	0.51

In Table 2 the overall mean absolute error (MAE) and root mean square error (RMSE) for SWAN numerical model and the NN are presented. The errors reduction is very significant. With this NN, we could achieve 83% reduction of the RMSE of significant wave height and 78% reduction for the mean wave period, in relation with SWAN model simulations.

Having a clear indication that the developed NN produce more accurate predictions of Hs and Tz on the location of the buoy, the networks were introduced in the warning system architecture and the whole domain results of the 3rd SWAN nested grid are corrected using a simple correction factor given by the percentage difference between NN and SWAN computed parameters. The whole subsequent calculations made by the EWS, wave propagation into the port domain and the forces and motions of the ships are thought to be more accurate as well.

FINAL REMARKS

Based on offshore forecasts computed by accurate weather-oceanographic forecasting models, the SAFEPORT-Sines EWS estimates the relevant wave parameters for the assessment of the behavior of ships moored within port basins, using a set of numerical models. The EWS issue alerts associated with danger levels for the ships' motions and forces on their mooring lines. The results are disseminated through digital platforms, namely a web page and a mobile application developed under the BlueSafePort project. The prototype of the system is the port of Sines, more specifically the bulk liquid terminal, the multipurpose terminal and the container terminal. Three ships are modelled, i.e., an oil tanker, a general cargo ship and a container ship.

The effectiveness of this EWS depends essentially on the accuracy of the atmospheric and wave forecasts and of the numerical models for wave propagation and for the moored ships behavior, being therefore subject to errors related to the models (parameterization, approximations, etc.) and to the boundary conditions imposed to those models.

In this paper neural networks were trained to reduce these errors and optimize numerical wave prediction models.

The trained neural networks were able to produce more accurate estimates for the significant wave heigth and mean wave period, at the buoy location, deployed in front of the Sines Port. The use of the new NN leads to an overall reduction of the RMSE of around 80% compared with SWAN numerical model simulations. Therefore a better estimation of the wave charactersitics in front of the port can be achieved and consequently a more accurate estimation of the mooring forces of the ships can be found. The use of these NN brings more reliability and robustness to the EWS.

ACKNOWLEDGMENTS

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