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

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INTRODUCTION

Within the BlueSafePort project an Early Warning System (EWS) is being developed for forecasting and alerting emergency situations related to ship navigation in ports, as well as operational constraints. Port terminals downtime leads to large economic losses and largely affects the port's overall competitiveness. So, 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. To achieve more accurate predictions a new method was developed to optimize forecasts produced by the system. Using available database from buoys, pressure sensors and meteorological stations, neural networks were trained to optimize numerical models results.

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. Given its national relevance, its continuous economic growth and constant expansion, the port of Sines has been the subject of several research projects. The prototype of the SAFEPORT EWS, for example, has been developed and validated for the Port of Sines. For that, SWAMS - *Simulation of Wave Action on Moored Ships* (Pinheiro *et al.* 2013) an integrated numerical tool capable of simulating the response of a moored ship within a harbor, subjected to the action of sea waves, wind and currents, was used to simulate the behavior of three different ships docked and moored at three terminals of the Port of Sines, namely: an oil tanker at the TGL, a general cargo ship at the TMS, and a container ship at the TCS (**Error! Reference source not found.**). Table 1 presents general geometric characteristics of the simulated ships as well as the mooring arrangements that are part of the EWS implemented and in operation.

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

EARLY WARNING SYSTEM

The SAFEPORT EWS follows a series of EWS from the HIDRALERTA platform which includes three Azorean ports: Praia da Vitória, S. Roque do Pico and Madalena do Pico, (Poseiro, 2019 & Pinheiro et al., 2020), and five other ports in mainland: Ericeira, Costa da Caparica, Peniche, Faro and Quarteira. Now an upgrade is being developed for the port of Sines using neural network tools for calibrating the wave propagation models.

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. These numerical models provide estimates of wave and wind characteristics in all domains, from regional scales simulated with several nested grids with SWAN model (Booij et al., 1996), to local scale, using a non-linear boussinesq-type model or a linear mild-slope model. Finally, the ship's response to those wave and wind forcings is computed using a hydrodynamic 3D panel method model (Korsemeyer et al. 1988) and a motion equation solver.

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. Hazard levels depend on the Maximum Breaking Load (MBL) of the mooring lines (OCIMF, 1992). 0 corresponds to no danger (green symbol), 1 corresponds to 50% of MBL (yellow symbol), 2 corresponds to 80% of MBL (orange symbol) and 3 corresponds to 100% of MBL (red symbol). Finally, based on the forecasted risk level, emergency situations as well as port operations' safety can be foreseen in advance (72h) and the adequate warning alerts can be issued.

All information provided by this EWS is available in a dedicated website and mobile application. 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.

WAVE MODELLING

The wave propagation medolling includes 3 numerical models for wave propagation and a finite element mesh generator. The numerical model SWAN is a spectral nonlinear model based on the wave action conservation equation, which simulates the propagation of irregular wave spectrum, transfers the wave characteristics from the offshore area to the harbor entrance. To transfer the wave characteristics from the harbor entrance area to the harbor's interior the EWS uses DREAMS and BOUSS-WMH. 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 model. The BOUSS-WHM model, (Pinheiro et al., 2011) is a nonlinear finite element model, based on the extended Boussinesq equations deduced by Nwogu (1993), being able to simulate the propagation of regular and irregular waves.

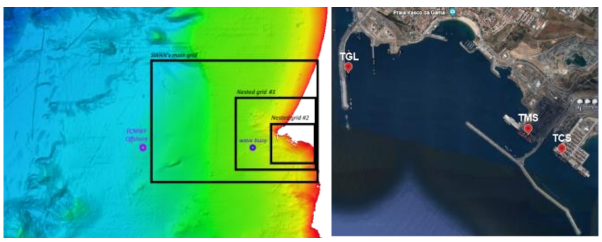

Figure 1 - Port of Sines. Left: Bathymetry of the surrounding area and the computational SWAN domains. Right: Location of the terminals.

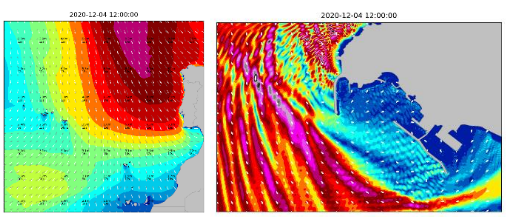

Figure 2 - Wave and wind forecasts. ECMWF-WAM forecasts (right). DREAMS model results (left)

NEURAL NETWORKS

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).

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. A NN is composed of an input layer, a number of hidden layers, and an output layer. Each layer has a certain number of nodes. Nodes in hidden layers are neurons. The neurons are distributed in several hidden layers which apply different transformations to the input data. 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.

Five input layers were used for the development of these NN. 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. 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.

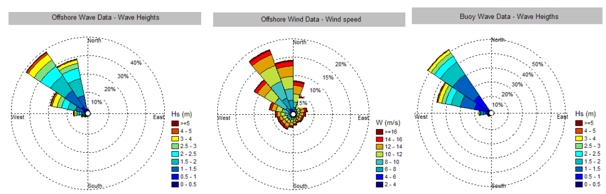

Figure 3 - Offshore wave (left) and wind (center) statistics. Buoy measurements wave statistics (right). Data period from 1988 to 2018.

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.

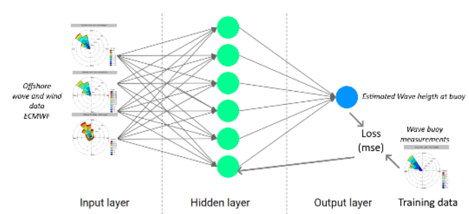

Figure 4 - Structure of the Neural Network for the wave height estimation/forecast at the Sines Buoy.

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. With this NN, we could achieve 83% reduction of the RMSE of significant wave heigth and 78% reduction for the mean wave period, in relation with SWAN model simulations.

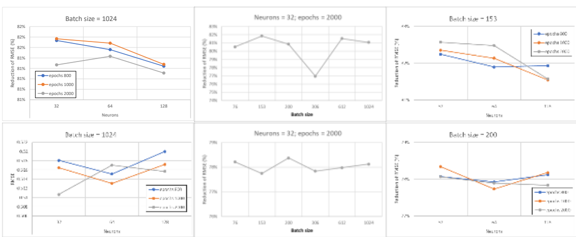

Figure 5 - Three stages of NN parameters optimization. Top: H; Bottom - Tz.

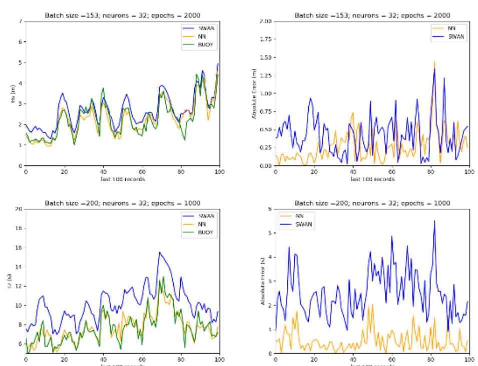

Figure 6 - Comparison of the last 100 records of the Buoy measurements, Neural Network output and SWAN numerical simulations. Top: Significant wave height; bottom: Mean wave period. Right: absolute error.

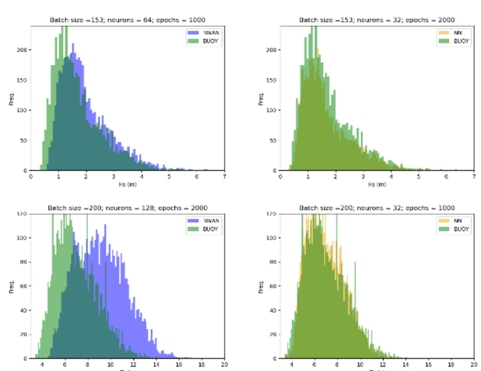

Figure 7 - Comparison of the frequency histograms of Buoy measurements, Neural Network output and SWAN numerical simulations. Top: Significant wave height; bottom: Mean wave period.

FINAL REMARKS

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.

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