WIND AND WAVE TRAINED ARTIFICIAL NEURAL NETWORKS FOR THE FORECASTING OF WAVE CLIMATE IN HARBOUR AREA

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Nowadays, maritime transportation has expanded rapidly, involving the need to enhance several navigation-related issues, particularly concerning the safety of navigation, which is significantly impacted by weather conditions. In this regard, creating a wave forecasting system could facilitate vessel movement at the harbour entrance or inside the sheltered area. Wave characteristics are usually estimated using numerical models, which generally require high computational costs, making them inadequate for nowcasting and forecasting wave climate. The current study describes the implementation of a forecasting methodology for the port area of Augusta (Sicily) based on an Artificial Neural Network (ANN) that attempts to deliver a trustworthy response and the numerical model but with a significant reduction in the computational time.

Keywords: Artificial Neural Networks; maritime accidents, SWAN, wave climate.

INTRODUCTION

The marine industry is the primary mode of transportation for both goods and people. Indeed, it powers nearly 90% of world trade, and over the past ten years, it has grown consistently at a rate of about 3% each year, stopped only by the COVID-19 pandemic in 2020 (UNCTAD/RTM, 2022). Therefore, ports play a strategic role in world trade, provided that some few well-known pressing challenges remain unsolved due to the continuous expansion of maritime traffic, such as reduced intermodality, poor digitalisation of processes, complexity of administrative procedures, backwardness of the development of green ports with a view to sustainability and, above all, limited safety of infrastructures. Indeed, the rise in ship numbers (Perera & Soares, 2017) and sizes (Tchang, 2020) that result from the increased maritime traffic also increases the risk of marine accidents. For example, ship collisions are the most common type of accident in ports, with an increased expected trend (Ozturk & Cicek, 2019). Risk analysis of maritime transport is receiving increasing attention to identify mitigation strategies (Marino et al., 2023). The statistical analysis shows that more than 80% of maritime accidents occur in the proximity of ports and are due to human errors (Sánchez-Beaskoetxea et al., 2021) and external causes, such as complex navigation environment, equipment failures and adverse weather conditions (Yu et al., 2021) that can generate problems related to the manoeuvrability of the ships (Zhou et al., 2020). Additionally, each port has unique physical and logistical factors, such as traffic density, bathymetry, or the current metocean conditions, influencing the various accident risk scenarios. In this framework, the availability of forecasting models, able to provide local weather and sea conditions well in advance and with sufficient precision, is undoubtedly helpful in mitigating the risk of accidents in port areas.

Complex numerical models, based on spectral approaches or Boussinesq or the mild slope equations, are usually used to define the wave climate in the proximity and within harbour areas. However, such models imply high computational costs and are unfit for forecasting and nowcasting systems (Salah et al., 2016). Artificial Intelligence algorithms, such as Artificial Neural Networks (ANNs), can be adopted to overcome this limit. Indeed, neural networks trained with data from the previously mentioned models can instantly provide the required meteomarine information. ANNs have been applied recently in several studies to forecast or hindcast sea states (Peres et al., 2015; Duan et al., 2020; Ma et al., 2021), storm surge (Kim et al., 2019; Qiao & Myers, 2021) or extreme waves (Dixit & Londhe, 2016; Fan et al., 2020).

The present work aims to show the results related to the implementation of ANNs for estimating the wave climate at specific points inside and outside the port of Augusta (Sicily), one of the most important Italian ports.

DESCRIPTION OF THE PORT OF AUGUSTA

The port of Augusta is placed on the East coast of Sicily, bounded to the North by a rocky headland and to the South by the Magnisi peninsula. The port presents a sheltered area of about 23 km^2, protected by 6.5 km of breakwaters and two port entrances: Levante and Passo Sud, exposed to the wave climate from the first and the second quadrant. The entrance of Levante has a width of about 480 meters, whereas Passo Sud has a width of about 260 meters. The average depth of the sheltered area is around 15 m, with a maximum draft of 21.8 m in the central area of the roadstead and an average depth at the operative piers of approximately 10 m. The wide harbour extent allows a maximum length of fetch of about 4.5

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km along the East-West direction and about 8 km along the North-South direction. Such large fetches within the harbour area, jointly with the action of local winds, can produce nonnegligible wave generation inside the harbour and additional threats for manoeuvring and moored ships.

Moreover, the maritime traffic inside the sheltered area of Augusta is intense, and official port accident reports show that 40% of accidents are due to the impact against elements such as buoys or docks, 25% are due to the collision between ships, and 30% is due to sinking and grounding. Adverse weather conditions are one of the leading causes of those accidents. Indeed, due to the sheltered area's muddy bottom and high wind speed from specific directions, adverse weather conditions frequently result in the displacement of anchored or moored ships, which causes collisions with other ships.

RECONSTRUCTION OF WAVE CLIMATE CHARACTERISTICS IN THE PORT AREA

The dataset adopted to train the neural networks were built using the numerical model SWAN (Simulating Wave Nearshore). It is a third-generation wave model, developed at Delft University of Technology, that computes random and short-crested wind-generated waves in coastal regions and inland waters (Booij et al., 1999) and that can simulate a variety of coastal processes, including wave breaking, wave shoaling, nearshore currents and wave-current interaction (Faraci et al. 2021).

The present study adopts an unstructured mesh to describe the computational domain. This type of mesh provides the opportunity to increase the mesh resolution in places of interest, such as close to or inside the harbours, and offers a far better depiction of complex boundaries than cartesian grids. Additionally, compared to cartesian grids, unstructured grids make it easier to describe the model area while maintaining high accuracy (Iuppa et al., 2015). Figure 1 shows the generated unstructured calculation grid of 30,080 triangular cells connected by 15,607 nodes.

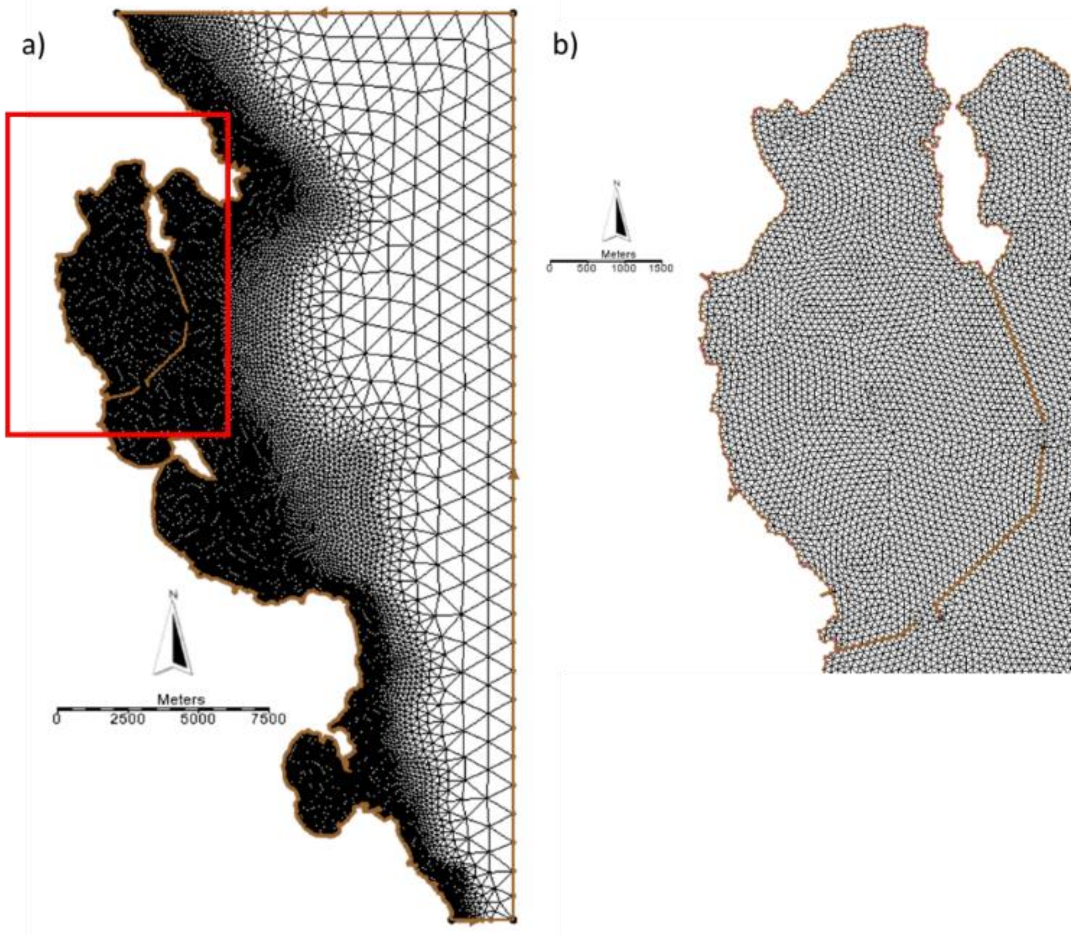

Figure 1. Computational domain of SWAN.

The European Centre for Medium-Range Weather Forecasts (ECMWF) and the Copernicus Marine Environment Monitoring Service (CMEMS) databases were used to gather information about wind and wave data without direct measurements. In particular, ECMWF wind data and CMEMS wave data are used here. The likely offshore scenarios have been defined as a result of examining these datasets to evaluate the characteristics of the wind and waves close to the port of Augusta. A synthetic overview of the two datasets is shown in Figure 2.

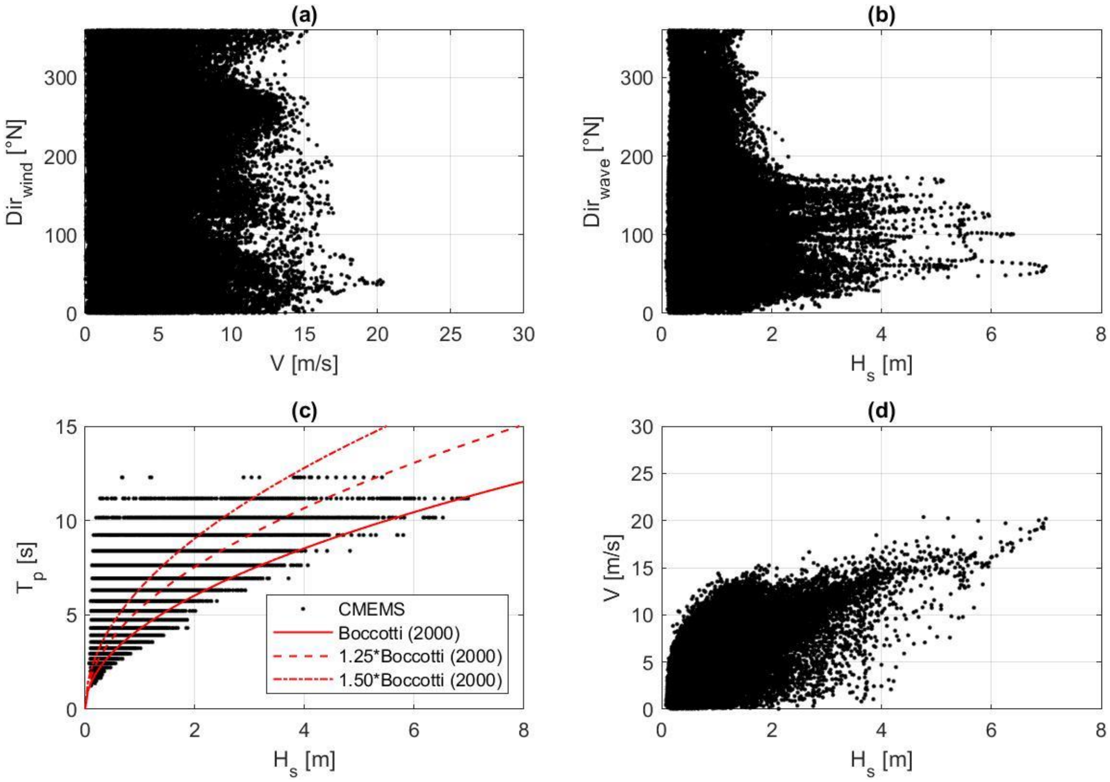

Figure 2. Analysis of the wind and wave data provided by the ECMWF and CMEMS respectively: a) wind direction as a function of the wind velocity; b) wave direction as a function of the significant wave height; c) comparison between the peak wave period estimated with Boccotti (2000) and that provided by the CMEMS; d) wind velocity as a function of the significant wave height.

According to Iuppa et al. (2022), 146875 scenarios were simulated with SWAN changing both the wind characteristics (velocity V and direction Dir_{wind}) and the wave characteristics (significant wave height H_s, mean direction Dir_{wave}, and peak period T_p). In particular, the analysis conducted by Iuppa et al. (2022) for the selected area showed that wave directions between 0 and 180°N (i.e. waves coming from the open sea) appear uncorrelated with local wind direction (Case 1), while wave directions greater than 180° (i.e. wave coming from the land) shows a significant correlation with local wind direction (Case 2).

The peak wave period was defined according to the relationship proposed by Boccotti (2000):

$$T_p = 8.5 \cdot \pi \sqrt{\frac{H_s}{4 \cdot g}}$$

where g is the gravity acceleration [m/s^2]. However, such a formula is strictly valid for the peak of a wave storm (Castro et al., 2022). Therefore, to consider other wave conditions, two other values obtained by increasing by 25% and 50% the value obtained with such a relationship were considered (see Figure 2 c).

For each simulated scenario, the execution time of each simulation was about 10 minutes using a computer with a RAM of 32 GB and an Intel(R) Xeon(R) Silver 4214 CPU @2.20 GHz.

Table 1 summarises the wind and wave characteristics provided as input for the numerical model SWAN.

Table 1. Wind and wave characteristics provided as input for the numerical model SWAN.

Case	Variables	Range	Step
Case 1 -wind direction coming from 0 to 360°N			
	Dir_{wind}	0-360°N	10°
	V	5 to 20 m/s	2.5 m/s
	H_s	0.5 to 7 m	0.5 m
	Dir_{wave}	15 – 155 °N	10°
Case 2 -wind direction coming from 180 to 360°N			
	Dir_{wind}	180-360	10°
	V	5 to 15 m/s	2.5 m/s
	H_s	-	-
	Dir_{wave}	-	-

CALIBRATION OF NEURAL NETWORKS

A set of feed-forwards MLP Multilayer Perceptron neural networks with one hidden layer was developed and trained with the back-propagation algorithm. Specifically, a neural network was built to evaluate wave climate generated by the wind that blows inside the sheltered area. A second one was created to forecast the wave climate near the port entrances.

The ANNs implemented on MATLAB using the Deep Learning Toolbox received the same input data as SWAN. Significant wave height (Hs), peak wave period (Tp), and mean wave direction (Dir) were extracted at the nodes of the calculation grid shown in Figure 3. In particular, among the nodes of the calculation grid, nodes E1, E2, E3, E4, E5, E6, E7 and E8 were selected as representative of the wave conditions outside the port. These nodes were identified in correspondence with the Xifonio port (E1, E2), the eastern entrance of the port (E3, E4, E5), the southern entrance of the port (E6, E7) and in the correspondence of the Seno di Priolo (E8). Furthermore, four nodes within the port were selected. Node I1 is close to Augusta’s commercial and military ports. Nodes I2 and I4 are close to the industrial port. Finally, node I3 is located near the eastern entrance of the port. The data relating to the O1 node were used to define the input data for the neural networks.

The whole dataset was divided into three sub-datasets: 75% for the training of the network, 15% for the validation and 15% for the test. The first two were adopted in the calibration phase of the neural network; the last one was used to compare different configurations of the ANN. In this application, the calibration was carried out using the Bayesian regularisation method, with the hyperbolic tangent as activation function in the input layer and the sigmoid one for the output layer.

The number of neurons in the hidden layer was changed from 1 to 150 to test different neural network configurations. The goodness of fitting was evaluated for each configuration using the Root Mean Squared Error (RMSE) to find the optimal configuration.

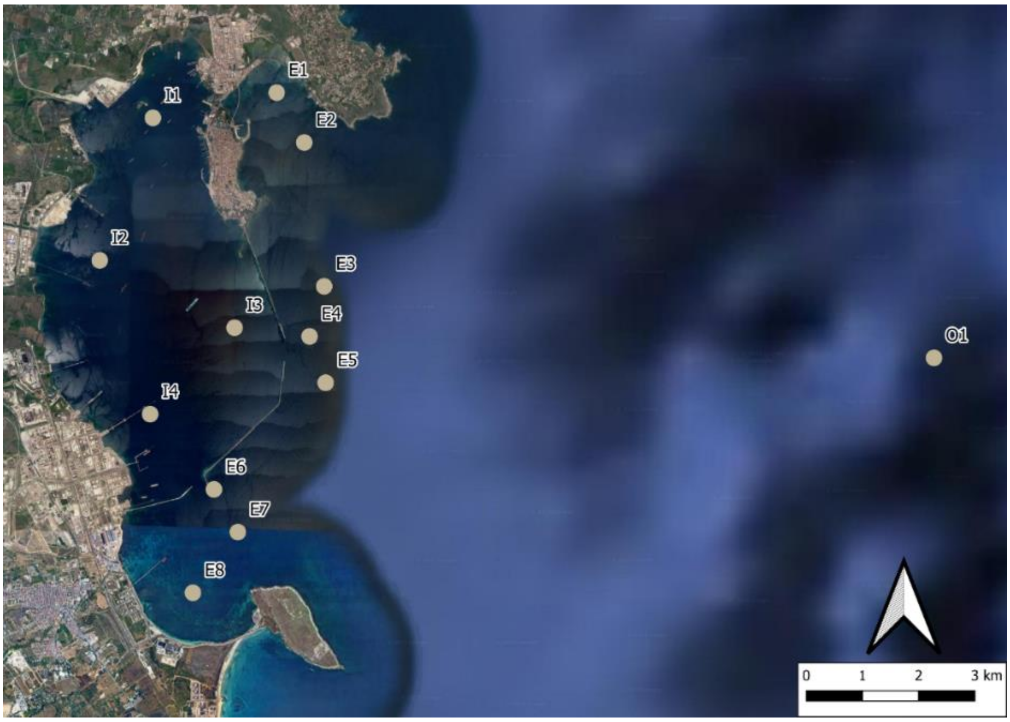

Figure 3. Computational domain nodes whose data has been adopted to calibrate neural networks.

RESULTS AND DISCUSSION

Regarding the setup of the neural networks, an analysis was conducted to determine the optimal number of neurons.

As shown in Figure 4 and Figure 5, the optimal configuration of all the ANNs developed contains 100 neurons in the hidden layer.

The value of Δ was estimated with the following relationship:

$$\Delta(i) = \frac{RMSE_i - RMSE_{i-1}}{RMSE_{i-1}}$$

where $RMSE_i$ indicates the value of the RMSE evaluated for the *(i-1)-th* configuration, and $RMSE_{i-1}$ indicates the value of the RMSE evaluated for the *i-th* configuration.

For all the considered nodes (external and internal to the port), both for the wave height and for the peak period, it is found that the error tends to remain constant for a number of neurons greater than or equal to 40. As far as the directions of the wave motion are concerned, more contained variations of Δ are found compared to those observed for the other two quantities. Also, in this case, for nodes external to the port, the number of neurons for which network performance is satisfactory equals 40. The configurations that guarantee the best performance for internal nodes are characterised by a number of nodes equal to or greater than 100.

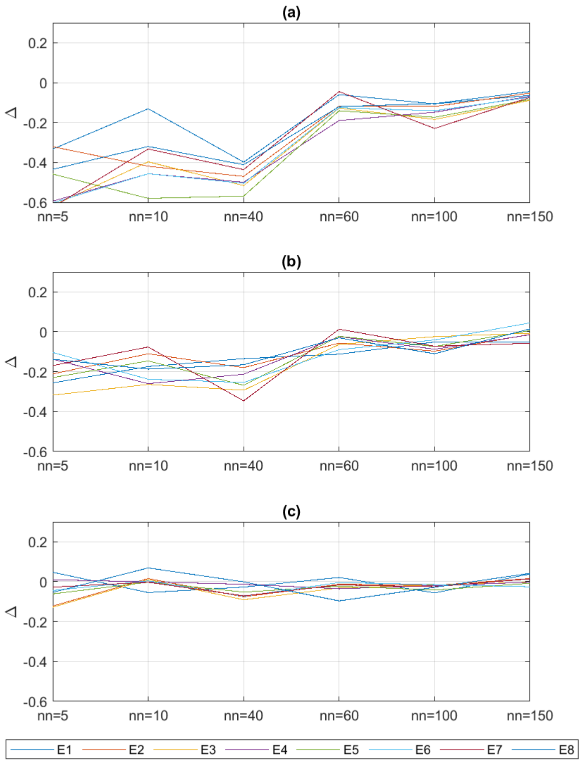

Figure 4. Points outside the port of Augusta. Variation of the RMSE as the number of neurons in the hidden layer varies: a) significant wave height; b) peak period of the wave; c) wave direction.

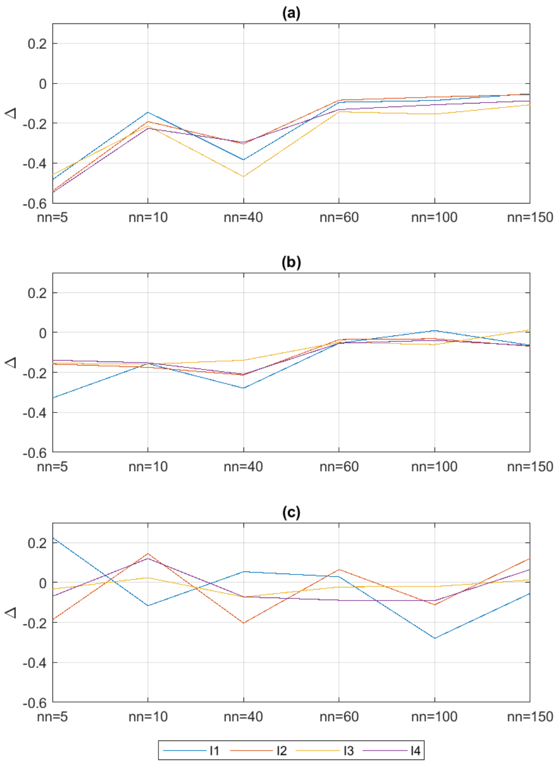

Figure 5. Points within the port of Augusta. Variation of the RMSE as the number of neurons in the hidden layer varies: a) significant wave height; b) peak period of the wave; c) wave direction.

To verify the reliability of the neural networks developed for the selected points, an entire storm that recently affected the port of Augusta was simulated through SWAN, considering the characteristics of storm waves as input data.

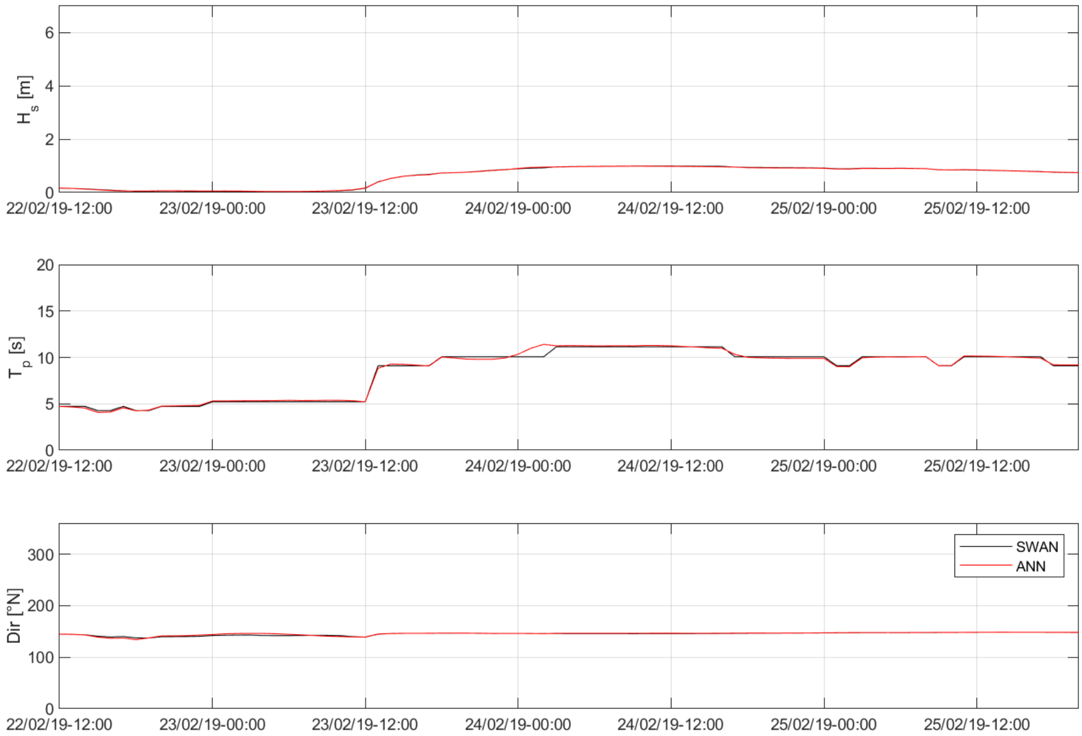

Figure 6. Node E1. Comparison between the results obtained by the neural network and the SWAN numerical model relating to the storm of February 24-25, 2019.

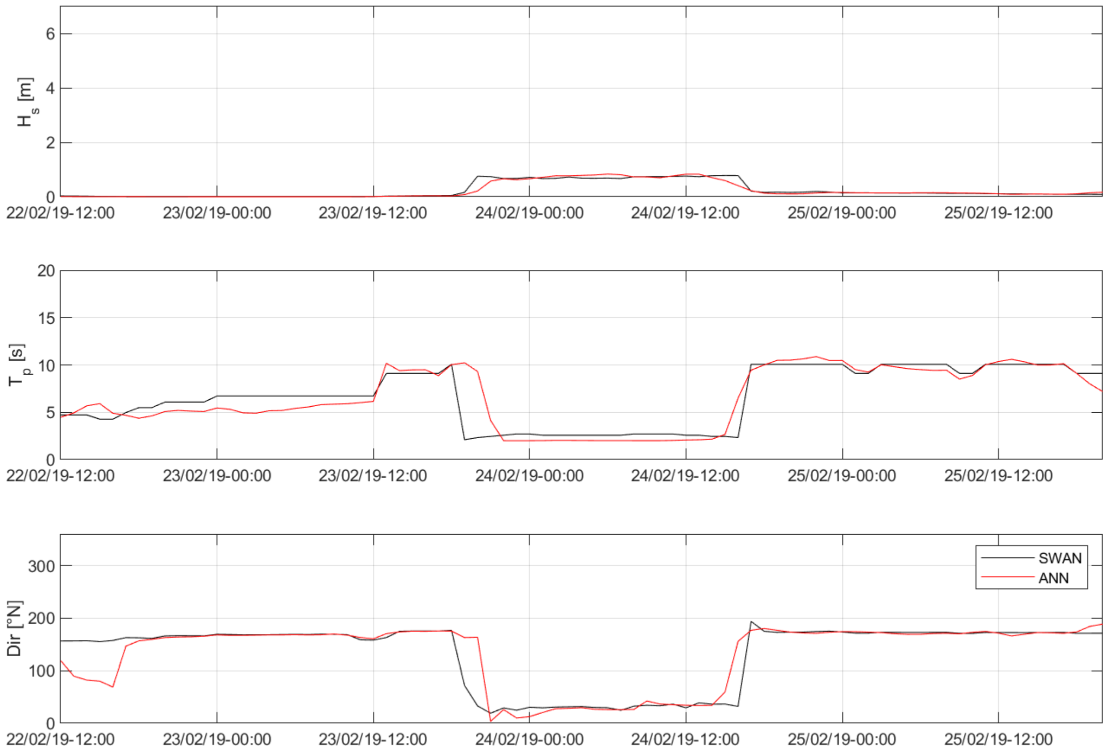

Figure 7. Node I1. Comparison between the results obtained by the neural network and the SWAN numerical model relating to the storm of February 24-25, 2019.

Table 2 summarises the root mean square error between the data obtained through the application of neural networks and those estimated through the SWAN. The comparison is limited to cases with a significant offshore wave height greater than 2 m. For all nodes, the characteristics of the wave during the storm were estimated with the ANNs' hidden layer composed of 100 neurons.

Table 2. RMSE evaluated by comparing the results of the neural network and the SWAN in the selected nodes.

Nome	*RMSE Significant wave height [m]*	*RMSE Peak period [s]*	*RMSE Wave direction [°]*
E1	*0.01*	*0.21*	*0.27*
E2	*0.04*	*0.14*	*0.45*
E3	*0.01*	*0.01*	*0.26*
E4	*0.02*	*0.07*	*0.37*
E5	*0.02*	*0.25*	*0.32*
E6	*0.03*	*0.21*	*0.44*
E7	*0.02*	*0.06*	*0.49*
E8	*0.01*	*0.14*	*0.17*
I1	*0.09*	*1.36*	*23.10*
I2	*0.05*	*0.88*	*5.88*
I3	*0.03*	*0.28*	*1.50*
I4	*0.03*	*0.30*	*1.38*

As shown in Table 2, neural networks allow a reliable estimate of wave characteristics. For the external points, the maximum error equals 0.04 m for the significant wave height, 0.25 s for the peak period and 0.5° for the wave direction.

The error tends to increase for internal points, especially for node I1. The error for such a node is equal to 0.09 m for the significant wave height, 1.36 s for the peak period and 23° for the direction of the wave motion. This difference is probably due to the location of node I1, which is relatively sheltered from the external wave. Therefore, it is more complex for the neural network to adequately define the functional link between the input and output data, especially for the less severe sea states. However, as seen in Figure 7, the neural network can adequately reproduce the wave's characteristics at the peak event.

CONCLUSION

Maritime transportation is strategically vital for the world economy. Consequently, its growth also contributes to an increase in the number and importance of marine accidents. Among the predisposing factors, adverse weather conditions play a leading role. In this perspective, being aware of the wave climate beforehand might reduce the likelihood of an accident and increase navigation safety. However, the modern spectral models used to calculate the wave climate involve long computational time, which is not compatible with the development of early warning systems.

The present work illustrates the results related to the development of neural networks for estimating the wave climate inside and outside the port of Augusta (Sicily) to implement a navigation aid system. The investigations carried out allowed us to assess how both the structure of the network and some training parameters of the network itself are essential for the accurate modelling of real conditions. Based on the analysis of the obtained results, it has been shown that the ANNs are an effective approach to be used for the safe management of port areas, allowing reliable forecasts of weather and sea conditions both outside and inside the port basin.

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REFERENCES

Boccotti, P. (2000). Wave Mechanics for Ocean Engineering. Elsevier Oceanography Series.

Booij, N., Ris, R. C., & Holthuijsen, L. H. (1999). A third-generation wave model for coastal regions: 1. Model description and validation. Journal of Geophysical Research: Oceans, 104(C4), 7649–7666. https://doi.org/10.1029/98JC02622

Castro, E., Santonocito, G., Moschetto, A. A., Iuppa, C., Musumeci, R. E., Cavallaro, L., & Foti, E. (2022). Artificial Neural Networks for the forecasting of wave climate in proximity of harbour area. In 2022 IEEE International Conference on Metrology for Extended Reality, Artificial Intelligence and Neural Engineering (MetroXRAINE) (pp. 618-623). IEEE.

Dixit, P., & Londhe, S. (2016). Prediction of extreme wave heights using neuro wavelet technique. Applied Ocean Research, 58, 241–252. https://doi.org/10.1016/j.apor.2016.04.011

Duan, W., Ma, X., Huang, L., Liu, Y., & Duan, S. (2020). Phase-resolved wave prediction model for long-crest waves based on machine learning. Computer Methods in Applied Mechanics and Engineering, 372. https://doi.org/10.1016/j.cma.2020.113350

Fan, S., Xiao, N., & Dong, S. (2020). A novel model to predict significant wave height based on long short-term memory network. Ocean Engineering, 205(December 2019), 107298. https://doi.org/10.1016/j.oceaneng.2020.107298

Faraci, C., Musumeci, R. E., Marino, M., Ruggeri, A., Carlo, L., Jensen, B., Foti E., Barbaro, G. & Elsaßer, B. (2021). Wave-and current-dominated combined orthogonal flows over fixed rough beds. Continental Shelf Research, 220, 104403.

Iuppa, C., Cavallaro, L., Vicinanza, D., & Foti, E. (2015). Investigation of suitable sites for wave energy converters around Sicily (Italy). Ocean Sci, 11, 543–557. https://doi.org/10.5194/os-11-543-2015

Iuppa, C., Cavallaro, L., Castro, E., Musumeci, R. E., Faraci, C., Carlo, L., Passalacqua, G. & Foti, E. (2022). Wave forecasts in the proximity of a harbour area based on artificial neural networks. In 2022 IEEE International Workshop on Metrology for the Sea; Learning to Measure Sea Health Parameters (MetroSea) (pp. 39-43). IEEE.

Kim, S., Pan, S., & Mase, H. (2019). Artificial neural network-based storm surge forecast model : Practical application to Sakai Minato, Japan. Applied Ocean Research, 91(June), 101871. https://doi.org/10.1016/j.apor.2019.101871

Ma, X., Huang, L., Duan, W., Jing, Y., & Zheng, Q. (2021). The performance and optimisation of ANN-WP model under unknown sea states. Ocean Engineering, 239(September). https://doi.org/10.1016/j.oceaneng.2021.109858

Marino, M., Cavallaro, L., Castro, E., Musumeci, R. E., Martignoni, M., Roman, F., & Foti, E. (2023). New frontiers in the risk assessment of ship collision. *Ocean Engineering*, *274*, 113999. https://doi.org/10.1016/j.oceaneng.2023.113999

Ozturk, U., & Cicek, K. (2019). Individual collision risk assessment in ship navigation: A systematic literature review. Ocean Engineering, 180(April), 130–143. https://doi.org/10.1016/j.oceaneng.2019.03.042

Perera, L. P., & Soares, C. G. (2017). Weather routing and safe ship handling in the future of shipping. Ocean Engineering, 130, 684–695. https://doi.org/10.1016/J.OCEANENG.2016.09.007

Peres D.J., Iuppa C., Cavallaro L., Cancelliere A., Foti E. (2015) Significant wave height record extension by neural networks and reanalysis wind data. Ocean Modelling, Volume 94, pages 128-140, ISSN 1463-5003, https://doi.org/10.1016/j.ocemod.2015.08.002.

Qiao, C., & Myers, A. T. (2021). Surrogate modeling of time-dependent metocean conditions during hurricanes. Natural Hazards. https://doi.org/10.1007/s11069-021-05002-2

Salah, P., Reisi-Dehkordi, A., & Kamranzad, B. (2016). A hybrid approach to estimate the nearshore wave characteristics in the Persian Gulf. Applied Ocean Research, 57, 1–7. https://doi.org/10.1016/J.APOR.2016.02.005

Sánchez-Beaskoetxea, J., Basterretxea-Iribar, I., Sotés, I., & Machado, M. de las M. M. (2021). Human error in marine accidents: Is the crew normally to blame? Maritime Transport Research, 2, 100016. https://doi.org/10.1016/J.MARTRA.2021.100016

Tchang, G. S. (2020). The impact of ship size on ports' nautical costs. Maritime Policy & Management, 47(1), 27–42. https://doi.org/10.1080/03088839.2019.1657972

UNCTAD/RTM. (2022). Review of maritime transport 2022. United Nations Conference on Trade and Development. https://unctad.org/system/files/official-document/rmt2022_en.pdf

Wang, N., Chen, Q., & Chen, Z. (2022). Reconstruction of nearshore wave fields based on physics-informed neural networks. Coastal Engineering, 176, 104167. https://doi.org/10.1016/J.COASTALENG.2022.104167

Wei, Z., & Davison, A. (2022). A convolutional neural network based model to predict nearshore waves and hydrodynamics. Coastal Engineering, 171, 104044. https://doi.org/10.1016/J.COASTALENG.2021.104044

Yu, Q., Teixeira, Â. P., Liu, K., Rong, H., & Guedes Soares, C. (2021). An integrated dynamic ship risk model based on Bayesian Networks and Evidential Reasoning. Reliability Engineering & System Safety, 216, 107993. https://doi.org/10.1016/j.ress.2021.107993

Zhou, Y., Daamen, W., Vellinga, T., & Hoogendoorn, S. P. (2020). Impacts of wind and current on ship behavior in ports and waterways: A quantitative analysis based on AIS data. Ocean Engineering, 213, 107774. https://doi.org/10.1016/J.OCEANENG.2020.107774