Artificial neural networks for significant wave height prediction

Armin Halicki[1], Aleksandra Dudkowska[1*]

[1]Institute of Oceanography, University of Gdańsk, Poland

[*]Corresponding author: aleksandra.dudkowska@ug.egu.pl

Abstract

Accurate estimation of wave parameters is essential for many maritime applications. Methods used in order to estimate crucial wave parameters (e.g. significant wave height, SWH), can be divided into numerical and regression models. Numerical models solve sets of differential equations, which makes them computationally expensive. Aditionally, very often they require calibration of empirical parameters as well as providing an extensive set of input variables. Therefore, they are often difficult to implement in real world applications. Regression models do not consider laws of physics explicitly, rather, they are used to find a statistical relationship between the target variable and a set of input variables. Depending on the required accuracy, they may have a relatively tiny set of input variables. This study focused on the prediction of SWH at point of interest with use of regression models, especially artificial neural networks (ANNs). Two groups of regression models were used. Autoregressive (AR) models, which rely only on the target variable to make the prediction, as well as multivariable (MV) models, which take external variables under consideration. ANN models were compared against benchmark models (ARIMA and naive). **Results of this study suggest that ANNs, especially recurrent neural networks (LSTMs, RNNs), are viable method for operational forecasting and can be effectively used in order to predict SWH with horizon of up to 12 hours, even when trained on data from different wind and wave regimes. Moreover, obtained results suggest that a reliable forecast within said horizon can be obtained even when using autoregressive models, thus eliminating the need for additional measuring devices.**

Materials and Methods

Source of data

Wave data included significant and maximum wave height, maximum wave height direction and period, peak wave direction and period and was measured with autonomous Directional Waverider MkIII buoy. Depth at buoy location was 18 meters and the distance from shore was 2 kilometers.

Wind data included wind speed, gusts and direction and was measured onshore with SW-42 anemometer.

Benchmark models

The performance of ANN models was compared against ARIMA [1] model after performing grid-search for parameter optimization. Additionally persistence (naive) forecast [1] was used as an additional benchmarking method.

Neural network training procedure

The training set for all of the models was composed from the first 80% of the data (1848 hours). The remaining 20% (456 hours) was used as a hold-out test set, which was used only during the final model assesment. In order to minimize overfitting, 5-fold nested origin crossvalidation [1] was used. For the neural networks three callback functions were used: reduce learning rate on plateau, early stopping and model checkpoint. The first method reduces the learning rate when training loss does not improve for prespecified number of epochs. This can allow to escape local minimum, which could be impossible with fixed learning rate. Early stopping halts model training when training loss does not improve for a prespecified number of epochs, actively preventing overfitting. For the same reason dropout technique [4] was used, which approximates training a larger number of neural network architectures in parallel. It does so by ignoring (dropping out) a prespecified percentage of neurons during training. In effect it introduces a larger noise into the training process, therefore increasing the generalization ability of trained network.

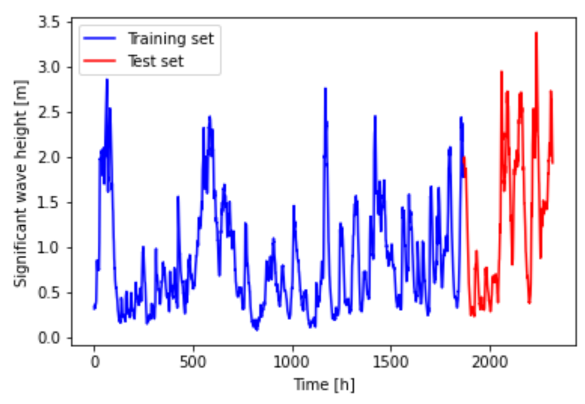
Hyperparameter optimization

All NN models were optimized with a grid search technique. Optimized parameters and their values are listed in the tables below. For multivariable models external variables in different combinations were also included in the optimization process. ARIMA benchmark models were also optimized, using Khandakar and Hyndman (2008) algorithm [2] within pmdarima Python package [3].

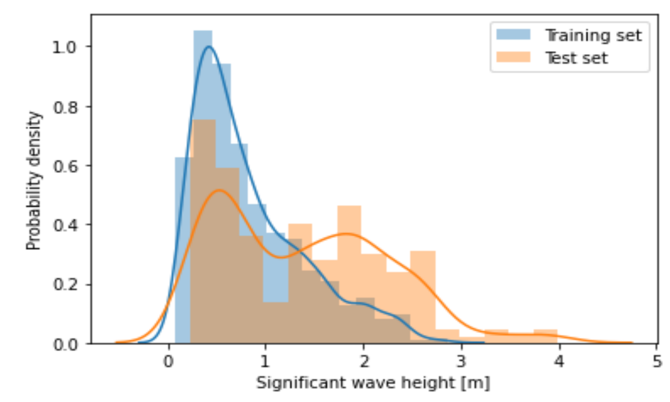
Hyperparameter	Values tested during optimization
# of hidden layers	[1, 2, 3]
# of additional dense hidden layers *(only in RNNs and LSTMs)*	[0, 1, 2]
# of neurons in hidden layers	[8, 16, 32, 64, 128, 256, 512, 1024]
# of hours included in history *(batch size for RNNs and LSTMs)*	[1, 3, 6, 12, 24]
Activation function in hidden layers	[ReLU, tanh]
Dropout regularization value	[0.0, 0.1, 0.3]

Combinations of external variables included in optimization procedure. ***(Previous significant wave height values were always included)***
a) Every variable separately. *(8 combinations)*
b) Unique combinations of up to three wind variables. *(4 combinations)*
c) Every variable measured by wavebuoy. *(1 combination)*
d) All available variables. *(1 combination)*

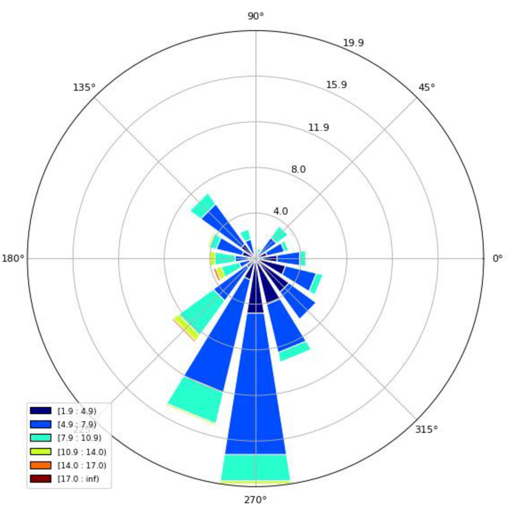
Comparison of training and test sets



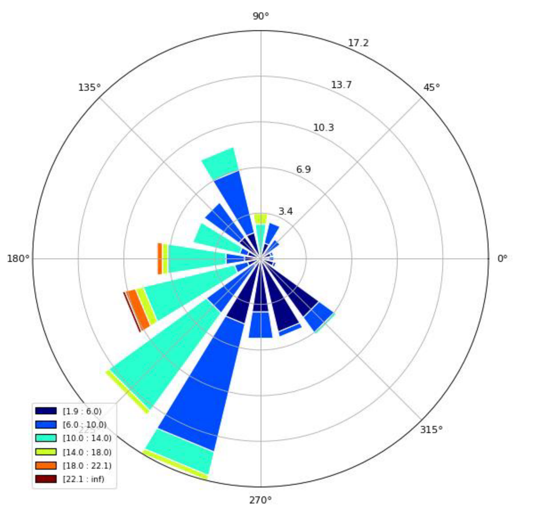
Time series of SWH (blue - training set, red - test set)



Distribution of SWH (blue - training set, orange - test set)



Wind rose (training set)



Wind rose (test set)

Results

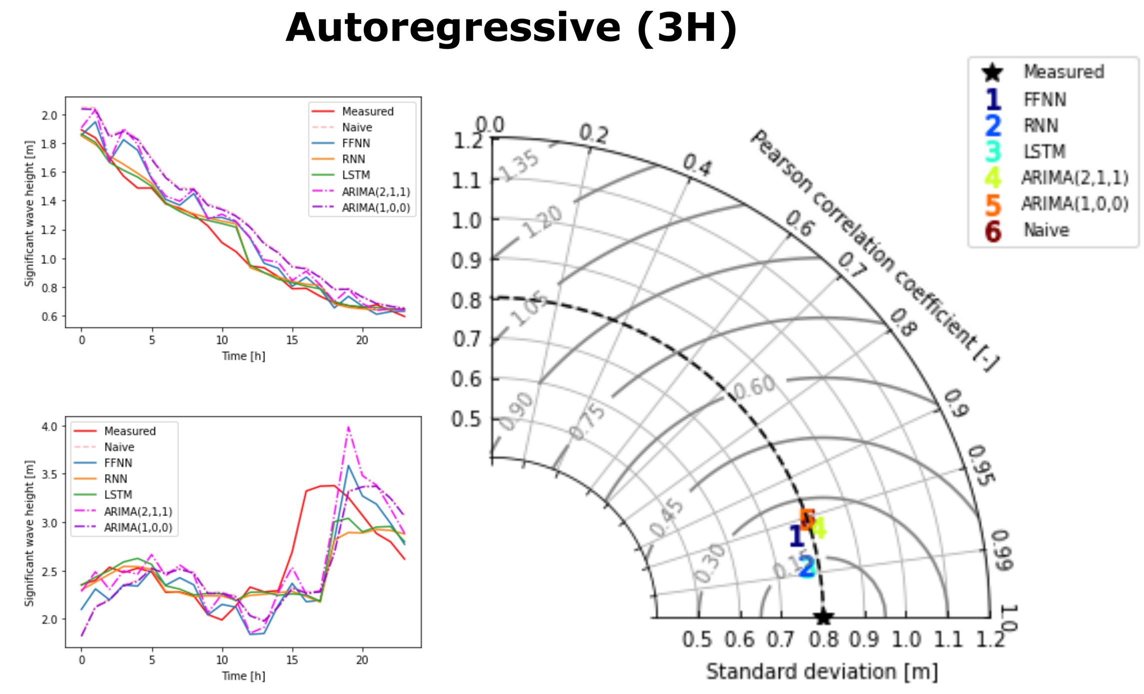
Best models for each horizon based on error metrics

Forecast horizon	Best model	Absolute RMSE	Relative RMSE
1H	RNN (AR)	0.08 [m]	6%
3H	LSTM (AR)	0.15 [m]	11%
6H	LSTM (AR)	0.23 [m]	17%
12H	LSTM (AR)	0.42 [m]	32%

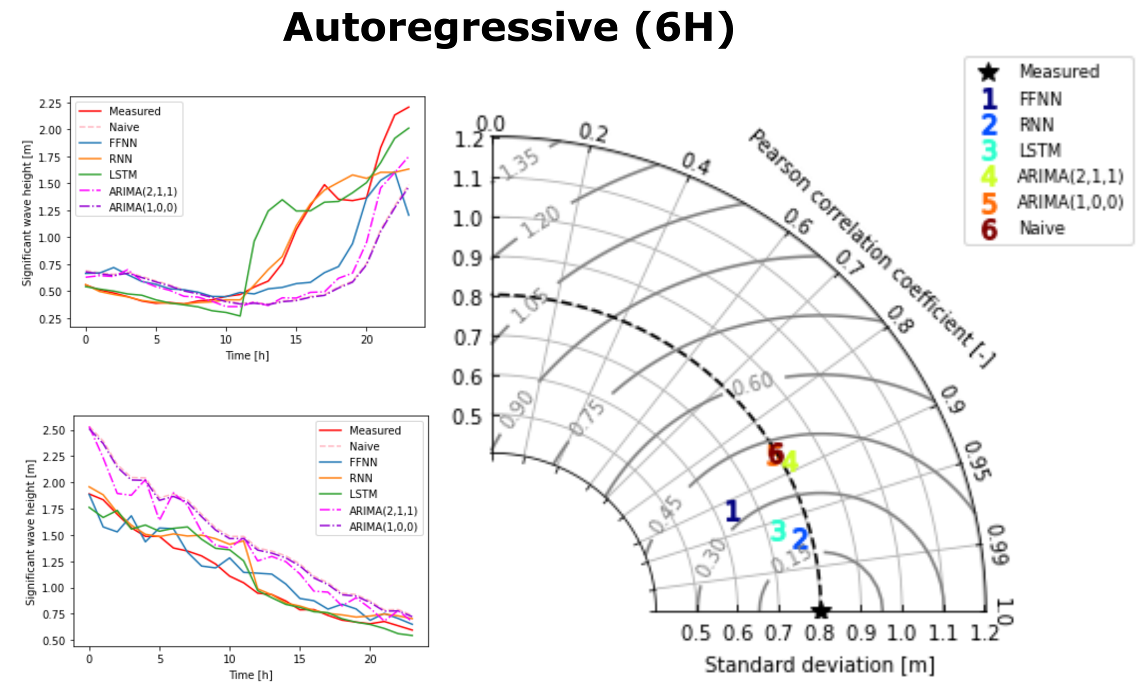
Forecast horizon	Best model	Absolute RMSE	Relative RMSE
1H	FFNN (MV)	0.08 [m]	6%
3H	LSTM (MV)	0.15 [m]	11%
6H	LSTM (MV)	0.20 [m]	15%
12H	LSTM (MV)	0.44 [m]	33%

Graphical comparison of forecasts

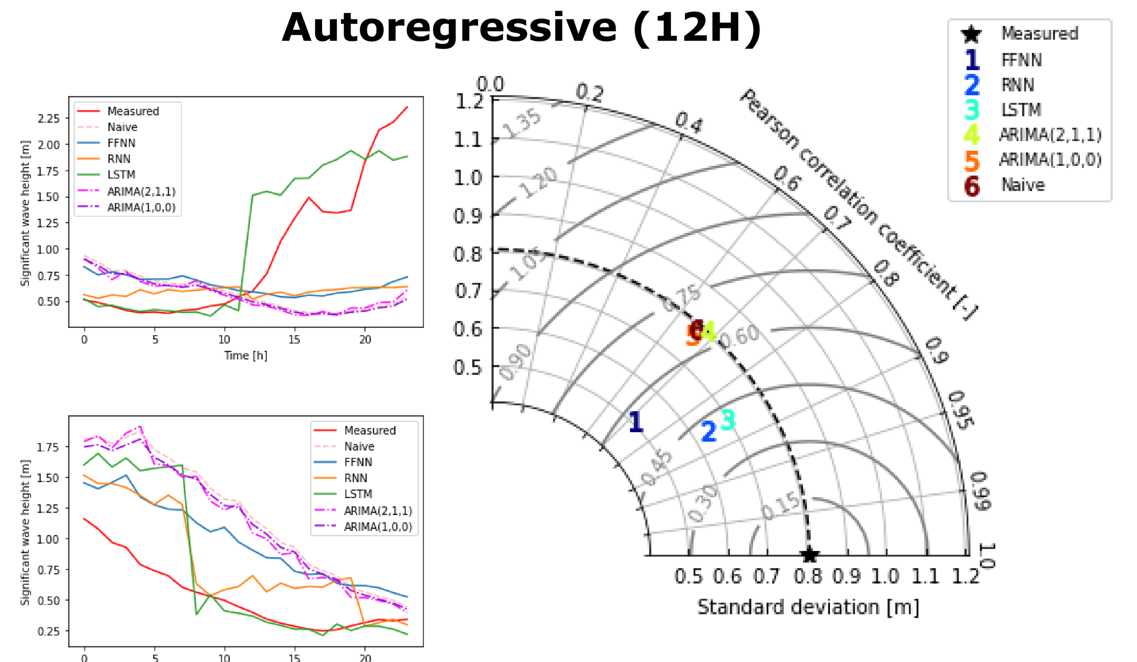
Autoregressive (3H)



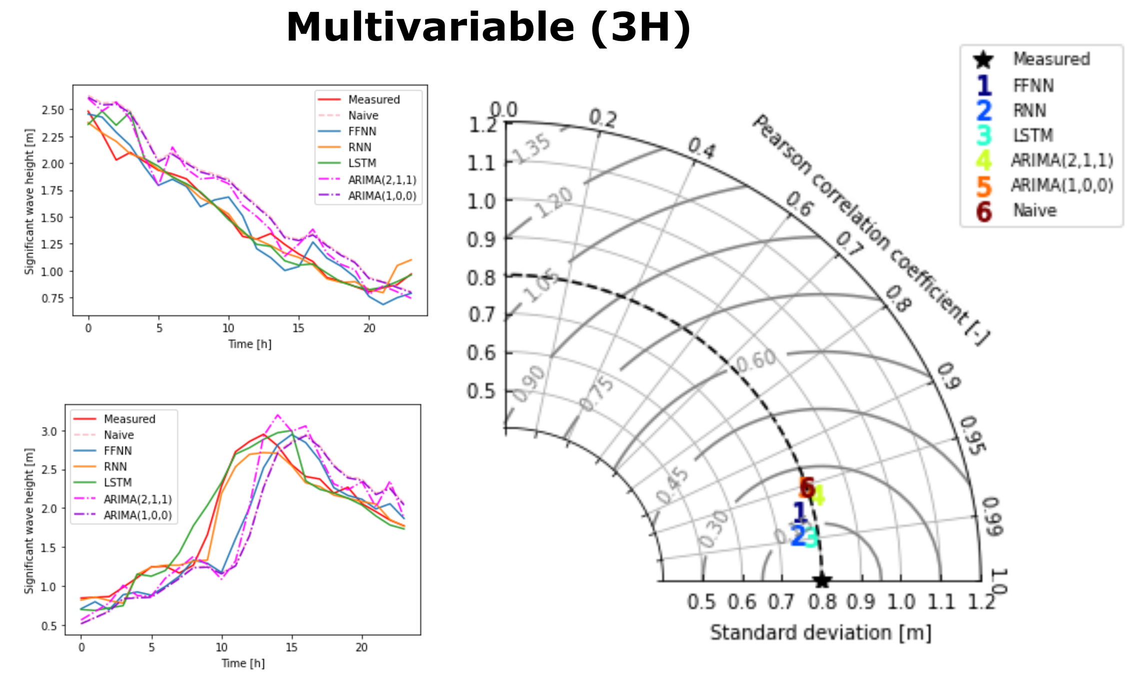
Autoregressive (6H)



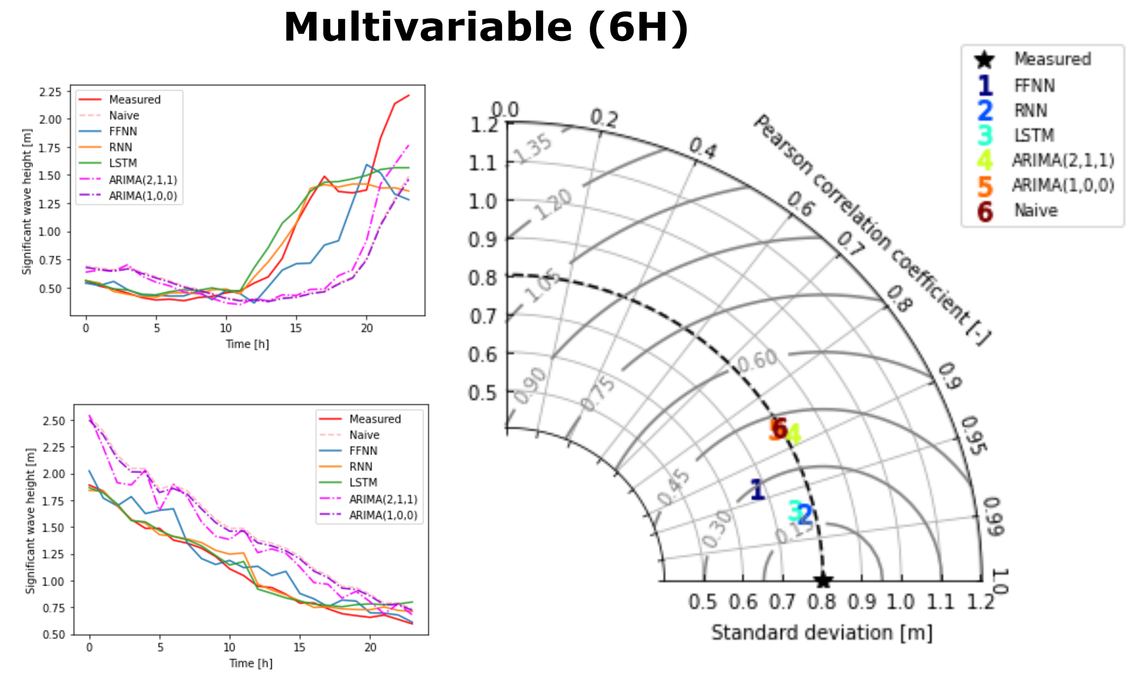
Autoregressive (12H)



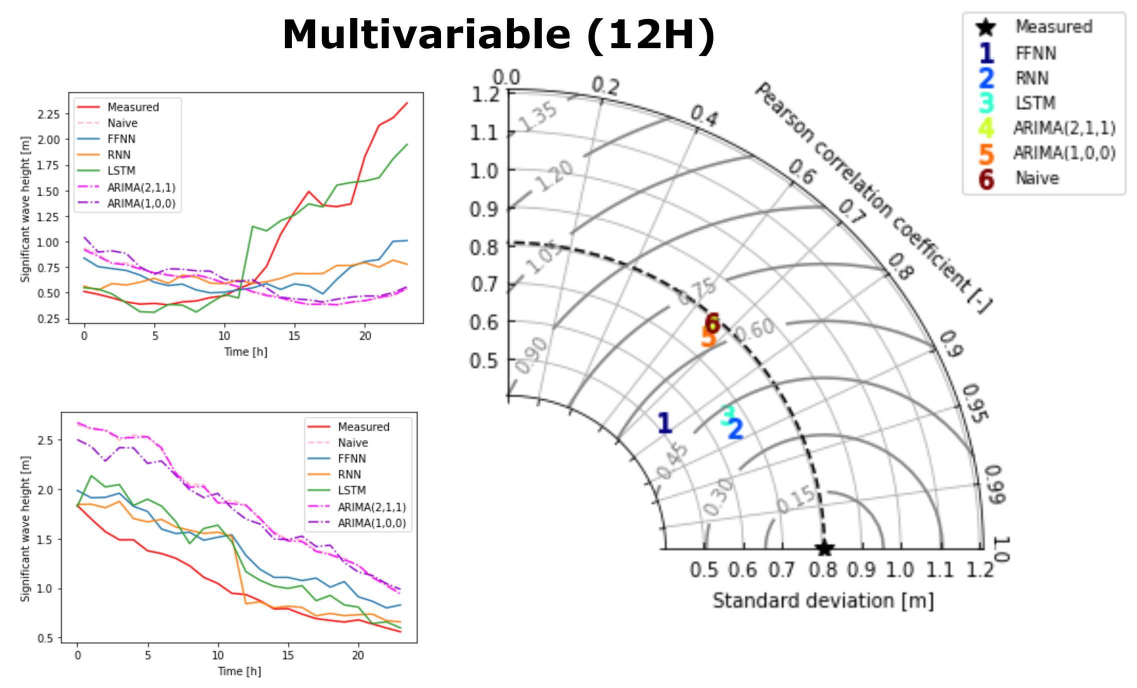
Multivariable (3H)



Multivariable (6H)



Multivariable (12H)



Conclusions

It is important to adress two fundamental issues when discussing the results of this study, both of which have great impact on the results. Firstly, the site depth (18 meters) makes it viable to assume that point of interest was located between the shallow and the deep sea in the terms of wave dynamics. Secondly, the training and testing sets differed in terms of the distribution of wave height and direction (Training set mean SWH: 0.83±0.55 [m], Test set mean SWH: 1.33±0.79 [m]) as well as wind speed and direction (as can be seen on the wind roses). **Recurrent neural networks (RNN and LSTM) proved the ability to maintain a reliable forecast with the horizon of up to 12 hours achieving smaller error metrics when compared with FFNN and other benchmark models, despite differences in prevalent wave and wind conditions between training and test sets.** Additionally, it has been shown that automated hyperparameter optimization and the **use of recurrent NNs can lead to overcoming the problem of a time-lagged forecasts** that can be often encountered in similar works [5]. Similar performance of autoregressive and multivariable models can be attributed to the fact of measuring wind on shore rather than in the same location as the wave parameters. Moreover, this result can lead to the conclusion that **autoregressive models are a viable option for short-term significant wave height forecasting, thus eliminating the need for carrying out continous measurements of external variables.**

Bibliography

1. Hyndman, R.J., Athanasopoulous, G., 2021, Forecasting: principles and practice, 3rd edition, OTexts, Melbourne, Australia (e-book), www.otexts.com/fpp3 (accessed: 21.06.2021).
2. Hyndman, R.J., Khandakar, Y., 2007, Automatic Time Series Forecasting: The forecast Package for R, Journal of Statistic Software 27(3).
3. Smith, T.G., 2017, pmdarima: ARIMA estimators for Python, http://www.alkaline-ml.com/pmdarima (accessed 21.06.2021).
4. Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., Salakhutdinov, R., Dropout: A Simple Way To Prevent Neural Networks From Overfitting, 2014, Journal of Machine Learning Research 15 (56), 1929-1958.
5. Dixit P., Londhe, S., Dandawate, Y., 2015, Removing prediction lag in wave height forecasting using Neuro-Wavelet technique, Ocean Engineering 93(1), 74-83.

Acknowledgements

The authors would like to thank the Institute of Hydro-Engineering of the Polish Academy of Science (IBW PAN) for providing access to long-term measurement data.