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Application of Neural Networks to the Prediction of Significant Wave Height at Selected Locations on the Baltic Sea

Barbara Paplińska-Swerpel, Łukasz Paszke

Institute of Hydro-Engineering of the Polish Academy of Science, ul. Kościerska 7, 80-328 Gdańsk, Poland, e-mails: bep@ibwpan.gda.pl, L.Paszke@ibwpan.gda.pl

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Abstract

This paper describes the application of methodology based on the artificial neural network technique to make short-term wave forecasts. The neural network model is used to predict significant wave height at a selected location on the Baltic Sea based on wave and/or wind data at ten points scattered on the sea. High quality hindcast data were used in the process of developing the forecast methodology. The data originated from the WAM4 wave model. The results show that the neural network technique allowed significant wave height to be predicted accurately. The agreement obtained by a comparison with a testing data set was sufficiently good to confirm the effectiveness of this approach.

Key words: sea wave forecast, neural networks, sea waves, Baltic Sea

Notation

d – neuron output,
h – linear activation function,
L – the number of multiple regression inputs,
N – number of samples,
$p_{1...L}$ – multiple regression inputs,
$w_{0...L}$ – multiple regression weights,
X, x – WAM4 model results,
Y, y – forecast results.

1. Introduction

This study was undertaken with the aim of meeting the requirements of a wide group of sea users for whom precise short-term forecasts of sea state are essential. The conventional wave models that resolve wave physics in a high-resolution grid, like WAM (WAMDI 1988) or SWAN (Booij et al 1999), require a high-resolution atmospheric model and considerable computational resources. The WAM4 wave model has been set up and validated in many locations throughout the world (Komen et al 1994) including the Baltic Sea (see e.g. Paplińska 1999). At the moment, neither the spatial resolution of these models nor the frequency of updates on operational wave forecast systems (usually six hours) are satisfactory. Thus, it is necessary to develop a fast, efficient, short-term local wave forecast method that is complementary to numerical models.

Neural networks are universal tools for the classification, approximation, control, and prediction of various phenomena. They are comprised of a set of artificial neurons linked together that work in parallel according to specific network architecture. This structure is able to capture and represent input-output relationships in data sets. Networks learn by example, based on training sets, and can generalize knowledge obtained. A well-trained net can predict output on the basis of input data that does not belong to the training set. Consequently, neural networks can predict many physical phenomena fairly well.

Neural nets have many applications in oceanography, including forecasting water level (Huang et al 2003, Sztobryn 2003). They also have several applications in wave forecasting (Deo et al 2001, Makarsky et al 2002, Medina, Serrano-Hidalgo 2005). In these works, wave parameters were forecasted using local wind or wave data for the forecast location as only these data were available. Improvement of the forecast accuracy was attempted by applying increasingly complex neural network models. Although the applications indicated the ability of neural networks to predict wave parameters on the basis of wind and wave data, the results of these forecasts are not satisfactory.

In addition to the tools applied, the choice of input data for the model also impacts the quality of the predictions. The primary factors shaping waves at sea are wind speed and duration. The waves in any location are the product of what is happening at any moment throughout the basin as well as what was happening there many hours previously. It would seem natural then to try to improve the quality of forecasts by widening the range of input data in the neural network model.

The most reliable source of data are in situ measurements. Only a few wave observation sites are in operation in the Baltic region at present, but there is great demand within the Baltic community for the establishment of further observation points (BOOS). Assuming that a system of buoys is in operation on the Baltic Sea in the near future, these buoys will provide real-time information on the Sea state and wind. These data will be utilized to forecast waves at any given location in the Baltic.

The aim of this research was to develop a method for making short-term wave forecasts that are quick and computer efficient and that permit the predictions of waves several hours in advance.

Due to the present unavailability of measured data, hindcast results instead of buoy measurements were employed in the current research to develop forecast methodology. Time series of significant wave height, mean wave direction, and wind speed and direction were simulated with the WAM4 wave model. The high quality hindcast data used were obtained within the framework of the EU project HIPOCAS (Hindcast of dynamic processes of the ocean and coastal areas of Europe, Soares et al 2002). The wind data originated from the REMO regional atmospheric model (Feser et al 2001), and the wave data came from the WAM4 wave model (Cieślikiewicz et al 2004, Cieślikiewicz, Paplińska 2005).

2. Data, Pre-Processing and Preliminary Statistical Analysis

The present study is based on Baltic Sea wave and wind modeled data for the 1989–1990 period. The data set consisted of the following four parameters:

- significant wave height,
- horizontal and vertical components of mean wave direction,
- wind speed,
- horizontal and vertical components of wind direction,

which were available every hour in the spatial grid of 5209 sea points with a resolution of about 5 Nm in the modelled area.

The original data set was transformed. It is known that the relationship between wave height and wind speed is quadratic (Massel 1996). Therefore, the wind speed parameter was raised to its square. Wave and wind directions are used in vector representation. Data regarding wave direction and wind direction were applied in the model as the horizontal and vertical vector components corresponding to wave height and wind speed respectively.

The preliminary statistical analysis was performed to obtain essential information for the construction of the prediction model. Based on data from the first 720 hours of 1989, correlation analysis was performed to analyze the spatial dependence of the significant wave height at a selected point – the point of interest (PoI in Fig. 1) on

a. the square value of wind velocity,
b. the significant wave height

at the 5208 remaining Baltic Sea grid points simultaneously.

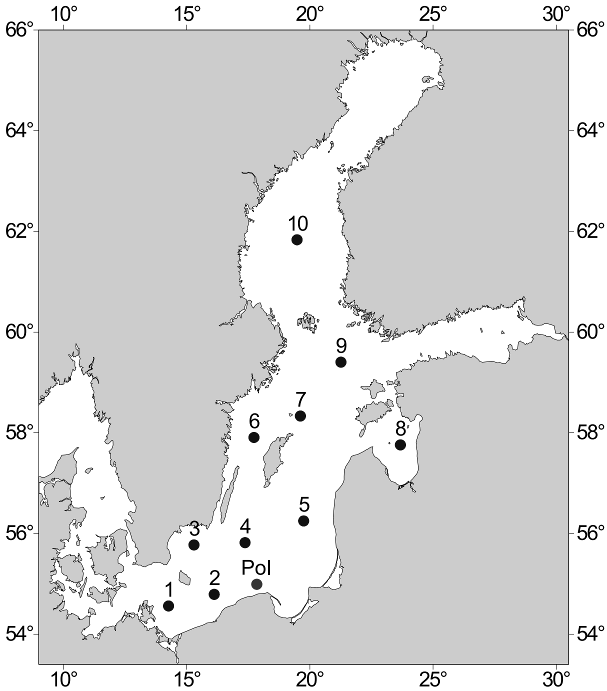


Fig. 1. Location of the data points on the Baltic Sea used in the present study

The localization of the PoI is not in any way unique, and every point on the Baltic Sea is equivalent. This point was chosen since it is near the Coastal Research Laboratory of IBW PAN and is located where the Waverider buoy takes wave measurements.

The results are presented in Fig. 2 as contour plots of the correlation coefficient between significant wave height at the PoI (cross) and squared wind velocity (a) and significant wave height (b). The maps show that there is a strong, long-range dependence between the data. Correlations between wave data are stronger than those between wind and wave data.

Time correlation analysis was also performed to analyze how the correlation between significant wave height and squared wind velocity or significant wave height changes with different time lags (from 1 to 72 hours). The analysis takes into consideration only significant correlations (greater than 0.5). The results are presented in Fig. 3. The figure presents maps of time lag for the maximum correlation occurrence at grid points on the Baltic Sea. The maps indicate that significant correlations for squared wind velocity occur at a 1–15 hour time shift (a) and at 1–63 hours for significant wave height (b). Long-term shifts in (b) occur rarely.

The very high correlations between these data indicate that a neural network can be appropriate for predicting significant wave height at chosen points using as input the time history of wave and wind data from points scattered on the Baltic

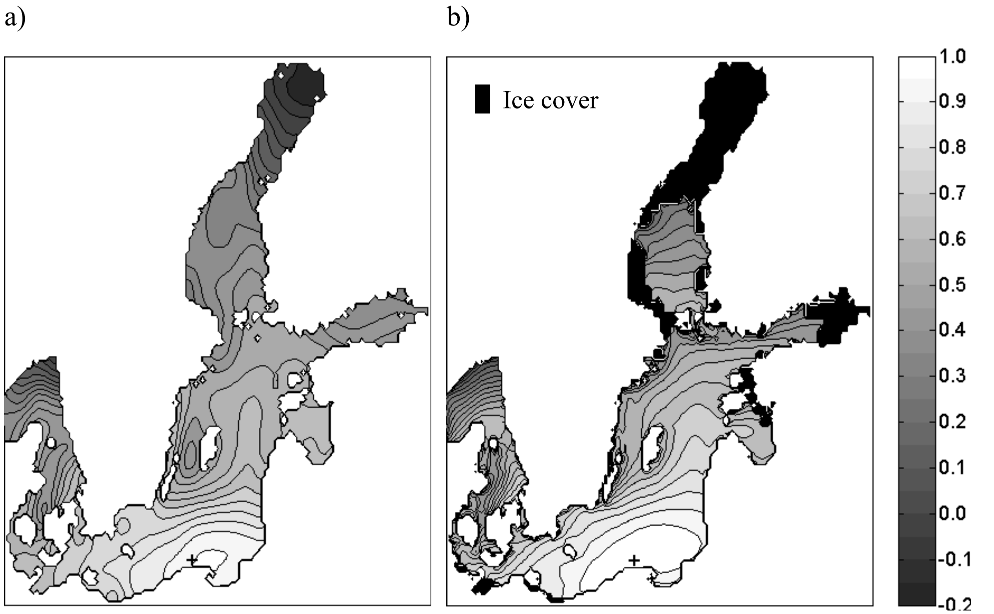


Fig. 2. Maps of correlation between significant wave height at PoI (cross) and a) squared wind velocity, b) significant wave height on the Baltic Sea

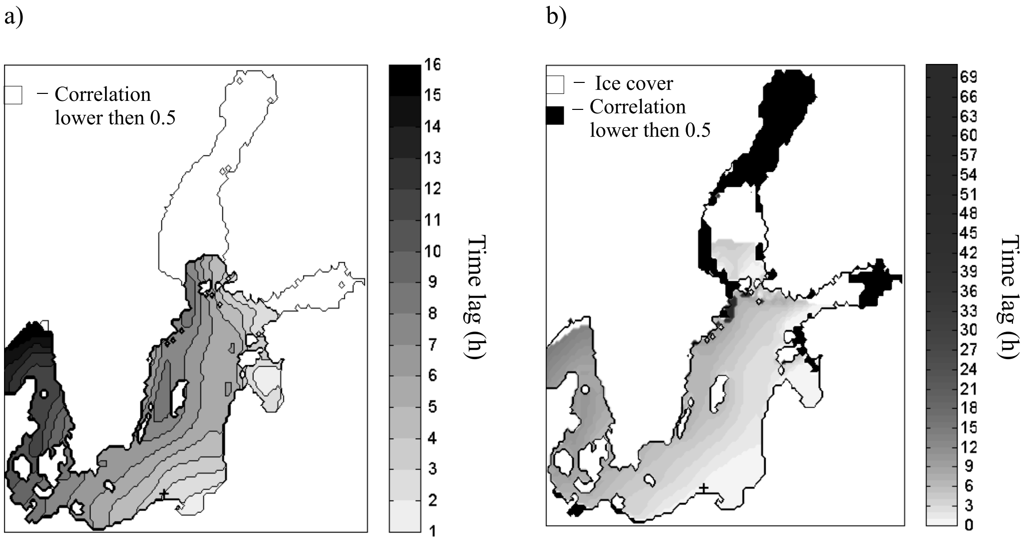


Fig. 3. Maps of time lag for the maximum correlation occurrence on the Baltic Sea a) squared wind velocity, b) significant wave height on the Baltic Sea)

Sea. The locations of points were chosen with respect to the results of correlation analysis. Point density is greater in areas where correlation is higher. The initial number of points was chosen intuitively in order to minimize the number while not excluding any information contained in either the wave or wind data. Testing of the significance of the chosen points will be presented in a later part of this paper.

3. Construction of the Neural Network

Determining the best wave prediction method was comprised of several stages. The work was begun by formulating modelled cases. Linear multiple regression was then applied. Sensitivity analyses were performed based on multiple regression. The results of these analyses were applied in the construction of various expanded neural networks.

3.1. Description of the Modelled Cases

The preliminary statistical analysis was the basis for formulating three prediction cases – A, B, and C. The three cases differ from each other with regard to input parameters:

Case A. (Number of inputs – 330)
at 10 points, 11-hour time history (1-hour time step) of:

- squared wind speed,
- horizontal and vertical components of the wind vector (normalized to the squared wind speed);

Case B. (Number of inputs – 330)
at 10 points, 11-hour time history (1-hour time step) of:

- significant wave height,
- horizontal and vertical components of the wave direction vector (normalized to unit);

Case C. (Number of inputs – 660)
at 10 points, 11-hour time history (1-hour time step) of:

- squared wind speed,
- horizontal and vertical components of the wind vector (normalized to the squared wind speed),
- significant wave height,
- horizontal and vertical components of the wave direction vector (normalized to unit).

In all the above cases a significant wave height at the point of interest PoI is predicted.

The following statistical parameters were used to measure the prediction performance.

- Bias

$$bias = \frac{1}{N}\sum_{i=1}^{N}(y_i - x_i) = \bar{y} - \bar{x}, \tag{1}$$

where:

N	–	number of observed and computed values,
x_i	–	WAM4 model value at time t,
y_i	–	the value computed with the regression model,
$\bar{y}, \bar{x}$	–	mean values.

- Root mean square error (RMSE)

$$RMSE = \left\{\frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2\right\}^{1/2}; \tag{2}$$

- Scatter Index

$$SI = \frac{RMSE}{|\bar{x}|}; \tag{3}$$

- Maximum error

$$MaxE = \max_{i=1...N}(x_i - y_i); \tag{4}$$

- Minimum error

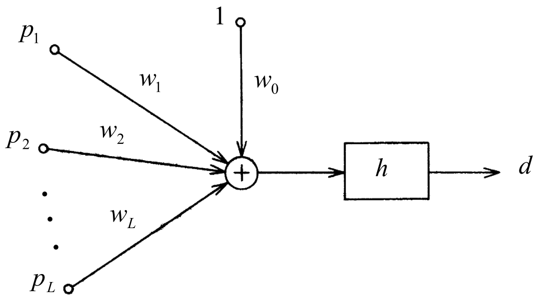
$$MinE = \min_{i=1...N}(x_i - y_i); \tag{5}$$

- Correlation coefficient

$$CC = \frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2\sqrt{\sum_{i=1}^{N}(y_i - \bar{y})^2}}}. \tag{6}$$

3.2. Linear Multiple Regression Method

Testing the applicability of neural networks for forecasting waves was begun by applying the linear multiple regression method which is identical to a simple neural network (Fig. 4). This network consists of one linear neuron and is trained using the multiple regression method (Jang et al 1997). The neural network is trained



$$d = h\left(\sum_{j=1}^{L} p_j \cdot w_j + w_0\right)$$

Fig. 4. One-neuron network, where $p_{1...L}$ – inputs, d – output, h – linear activation function, $w_{0...L}$ – neuron weights, L – number of inputs

for the considered cases to predict significant wave height at the point of interest PoI (prediction point).

Training was based on the consecutive hours of the year 1989. The training data set consists of approximately 9000 samples. The trained network was tested with the testing data set which consisted of the consecutive hours of the first quarter of 1990 (approximately 2000 samples).

Multiple regression was applied to a 4-hour forecast of significant wave height in these cases. The results are presented in Fig. 5. The plots show the comparison between predicted significant wave height and WAM4 model results for the testing data set. The testing data were independent and were not used in the network training process. The comparison reveals very good conformity of the forecast results and the WAM4 model output for all the models.

The worst results were obtained for case A, excluding minimal error, which is highest for the results from case B. The statistical parameters for case C are better than the corresponding ones for case B. This indicates that the prediction derived on the basis of wave data is better than that derived from wind data. This was expected since wave fields are correlated not only with wind, but also with wave history. Moreover, wave data comprise some information about wind and its influence on waves. Therefore, the relation between wave data at considered points is less complicated than that between wind and wave data. As a result, correlations between wave data are stronger than correlations between wind and wave data. Statistical comparison is shown in Table 2. Detailed analysis indicated that the quality of all cases is comparable.

The analysis of the behaviour of prediction quality with forecast length was carried out on case B. Multiple regression was applied to the 4–8-hour forecast

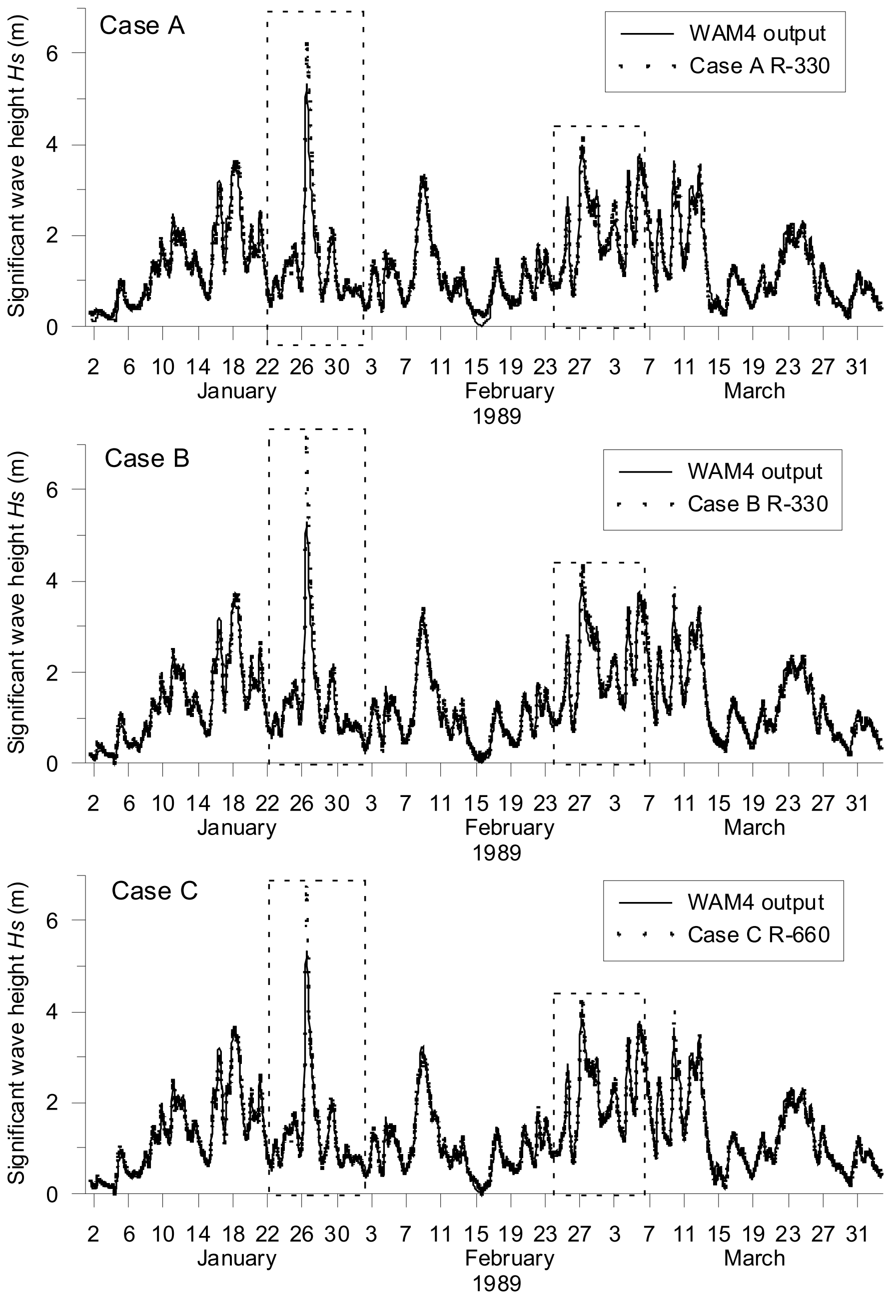


Fig. 5. Comparison of 4-hour forecast results (dotted line) obtained with the multiple regression method and WAM4 model output (solid line) for the testing data set. The numbers '330' and '660' indicate the number of inputs. Detailed comparisons during two stormy periods (marked with dashed rectangles) are shown in Figs. 9–12

of significant wave height. The results are shown in Fig. 6. The plots represent the statistical parameters (correlation coefficient, root mean square error) of the prediction in the testing data set. The results show that prediction quality declines as the forecast length increases. Although the correlation coefficient decreases from 0.98 to 0.94, its value remains very high.

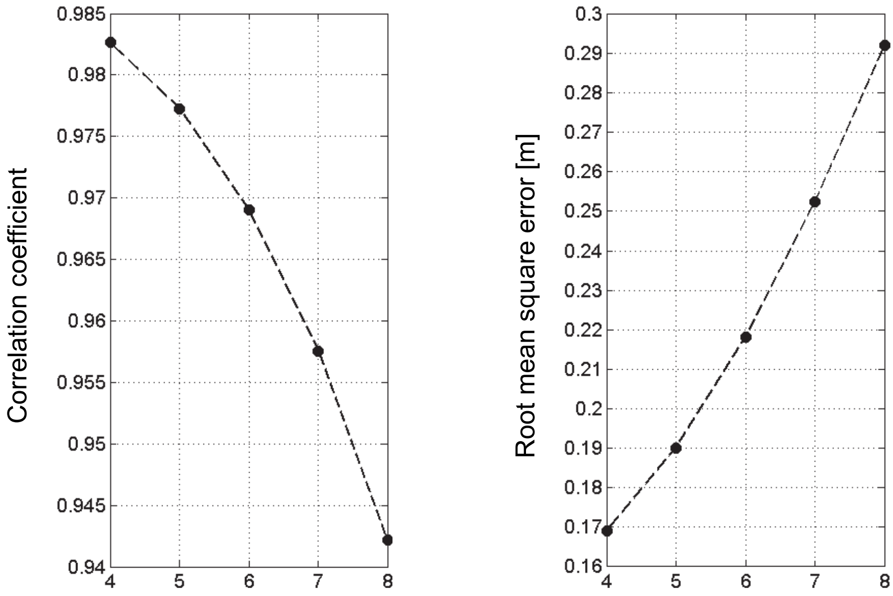


Fig. 6. Statistical parameters for 4–8-hour forecasts of significant wave height for testing data set (Case B)

Linear multiple regression models fed with first guess input data produced unanticipatedly good results. However, the greatest differences were noted during storms (see Fig. 5), which is precisely when high quality forecasts are needed the most. This provided the impetus for striving to improve the results of the forecast by limiting the input vector only to significant components and by elaborating the neural network.

3.3. Choice of Input Data – Sensitivity Analysis

Prior to applying more complicated networks, the regression performed was subjected to sensitivity analysis. The aim of the analysis was to identify the input data which had a real impact on the forecasting of significant wave height. Determining the hierarchy significance of individual inputs permitted the omission of unnecessary inputs, which decreased the computational complexity of the problem, and allowed for the use of a more complicated neural network. Additionally, adaptively fitting the network to insignificant parameters worsens prediction, which is why they should be removed from the input vector.

The method described by Engelbrecht et al (1995) was used to test sensitivity. This is based on determining the sensitivity of the i-th input on its output. The sensitivity S_i of trained output y with respect of an input x_i is defined as:

$$S_i = \sqrt{\frac{\sum_{k=1}^{N} \left[\partial y_k / \partial x_{i,k}\right]^2}{N}}, \tag{7}$$

where N is the number of training pairs. In the formula above it is assumed that all inputs are normalized. Sensitivity S_i obtained in this way is a measure of the significance of i-th input to output, thanks to which the most significant inputs can be separated from unnecessary ones. Histograms of significance of the multiple regression inputs presented in Fig. 7 were obtained based on the sensitivity analysis performed.

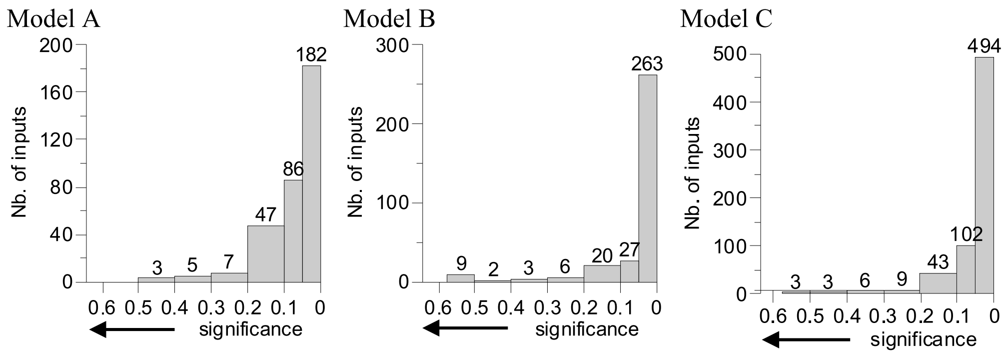


Fig. 7. Histogram of significance

These indicate that in all the cases a substantial number of inputs do not have much of an impact on the output. Sensitivity analysis was used to categorize the input data according to their significance, which permitted eliminating those that had a lesser impact on the output. The only thing remaining is to determine how many inputs should be included to obtain the best modelling result.

The linear multiple regression model was applied with various numbers of inputs thus eliminating subsequent inputs of increasing sensitivity. The modelling results were compared to the testing data set. Changes in the RMS error depending on the size of the input vector are presented in Fig. 8. It is clearly visible in case A that for 47 inputs the error is the smallest. In case C the minimum error for 100 inputs is slightly less distinct. Due to the occurrence of the minimum of

RMS error, the initial vector in models A and C was only increased to 200. Calculations were also performed for 330 and 660 inputs, respectively. The minimum error in case B is not as distinct. Thus, the case was tested for the full range of inputs up to 330. Increasing the initial vector in this case to above 147 does not improve the output.

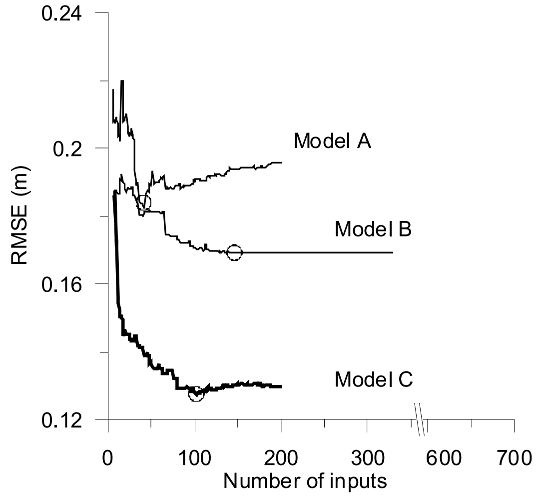


Fig. 8. Changes in the RMSE error in multiple regression linear models depending on the size of the initial vector. The optimal initial vector size for the multiple regression model is depicted with circles

In Fig. 8 the optimal initial vector size for the multiple regression model is represented with circles. The statistical parameters of the comparisons of cases A, B, and C with limited numbers of inputs of 47, 147, and 100, respectively, are presented in Table 2 in the next chapter. It can be concluded that substantially limiting the number of inputs improves the results of modelling with the help of cases A and C, but that case B does not change them.

3.4. Neural Network Method

Just like any problem in engineering, the prediction of waves can be reduced to the problem of predicting some parameters using others, i.e. to the multivariate approximation function. As is demonstrated in the work of Jang et al (1997), Duch et al (2000), Hertz et al (1991), neural network feed-forward (perceptrons) is very good for realizing such approximation tasks. The quality of prediction based on them depends largely on the choice of the appropriate structure (number of neural layers, the quantity of neurons in each layer). In the nomenclature of the present work, the input vector is not regarded as a neural layer in the network. As demonstrated by Hertz et al (1991), three neural network layers are sufficient to solve any given approximation problem. The question of calibration remains the choice of the number of neurons in a given layer. However, too many (leading to overtraining, interpolation, small capacity for generalization) as well as too few (leading to large prediction error) neurons in the various layers is not desirable.

To ensure the possibility of mapping linear and nonlinear relationships, neurons in the first hidden layer and in the output layers have a linear activation function, while the second hidden layer has a nonlinear sigmoid activation function.

The prediction error realized by the network was minimized by the use of the root mean square error, which is applied widely in solving approximation problems.

Of the available benchmarks (Demuth and Beale 2001), it appears that with approximation problems of comparable complexity to the problem under consideration in this work, the best training algorithm, as regards convergence and the length of time required for the training, is the Levenberg-Marquardt algorithm. However, as is the case with all neural networks and training algorithms, there is never any guarantee that the error obtained is the minimum which can be obtained based on the trained network (i.e., never is there complete certainty that the minimum error found is the global minimum). This is why training is repeated many times starting at random beginning states of the network (set of weights), in order to find the minimum that is closest to the local minimum. In the present work the training process was repeated 16 times using the Nguyen-Widrow algorithm (Nguyen and Widrow 1990) to draw the initial weights and which, in choosing the optimal initial weight range, takes into consideration the network architecture.

The network was then calibrated "by hand" by testing various structure combinations ($1 \div 8$ neurons in the first hidden layer, $1 \div 8$ in the second hidden layer, 1 neuron in the output layer) and the quantity of the most significant parameters; the goal was to determine which network produced the best prediction results. Based on generalization capability and prediction error, network I was chosen from among the tested networks. Its structure is presented in Table 1. The first linear hidden layer, which consists of four neurons, is capable of extracting four linear principal components from a signal. The second hidden layer is able to add on potential non-linearity (non-linear interactions between components), or the signal is allowed trough approximately in linear way. An output neuron serves as a weighted sum.

The networks were trained and tested for the same training and testing data sets as in the case of multiple regression method.

4. Modelling Results

Two storms with significant wave height over 3 m took place during the testing period (see Fig. 5). To illustrate performance of the models in severe conditions, time series plots for the stormy periods are shown in Fig. 9, 10, 11 for cases A, B,

Table 1. Network I structure

Network	Layers	Neurons number	Activation function
1	first hidden	4	linear
	second hidden	7	tanh
	output	1	linear

C respectively, and additionally in Fig. 12 the results of the best neural networks of all cases are shown altogether.

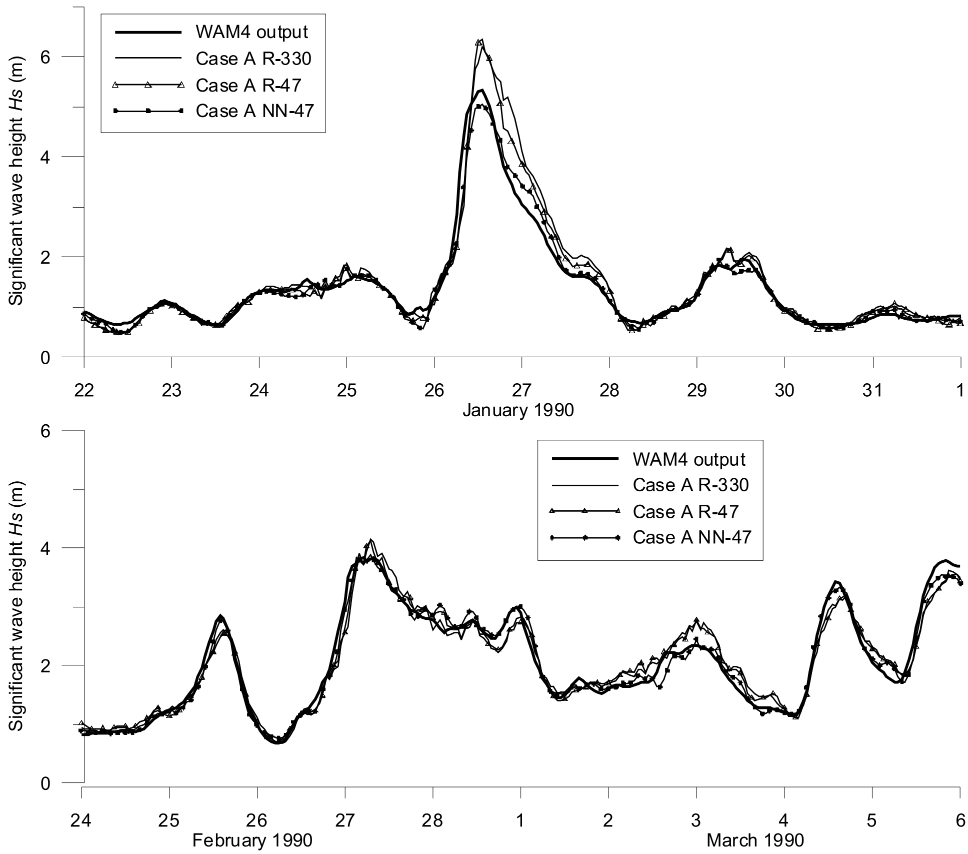


Fig. 9. Case A: 4-hour forecast of significant wave heights for two stormy periods obtained with the different methods

Statistical comparison between 4-hour forecasts of a significant wave height by means of neural network and the testing data set is shown in Table 2. The results of simulation of the best networks with reduced input vector (as described in the previous chapter) for the three cases: A, B, C are presented here together with the results of the multiple regression method with reduced and non-reduced input vectors.

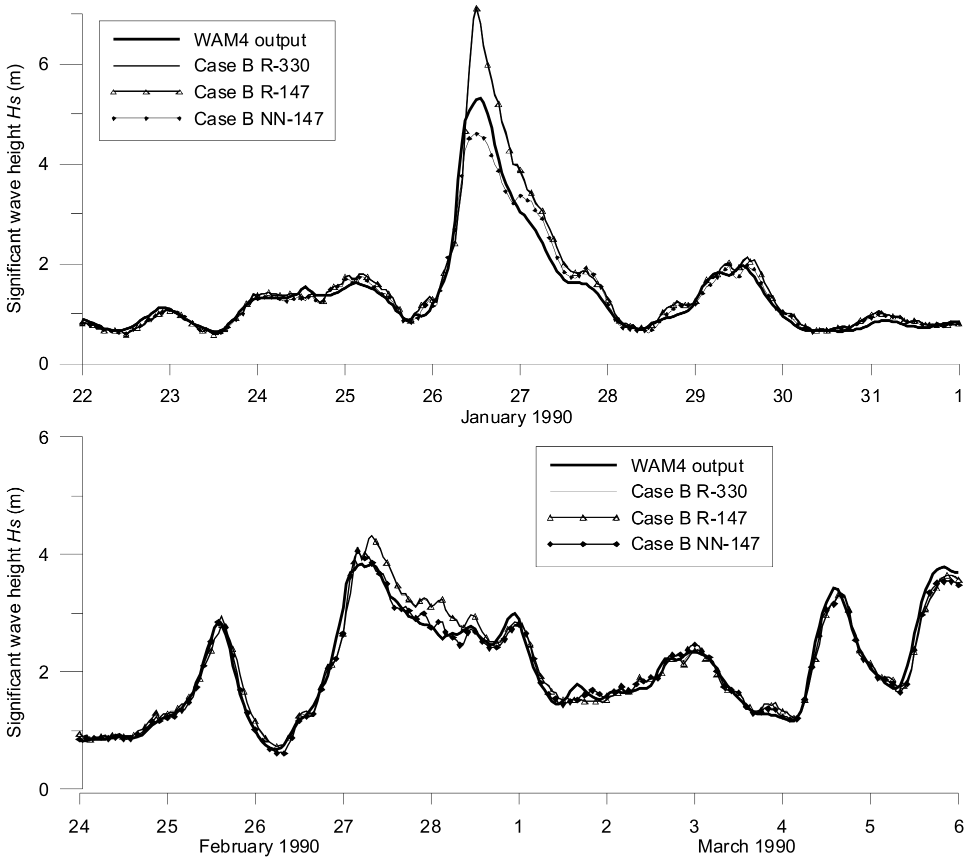


Fig. 10. Case B: 4-hour forecast of significant wave heights for two stormy periods obtained with the different methods

Fairly good predictions of the significant wave height were produced for all formulated cases. The results of described neural networks models with reduced input vectors show sufficient improvement in comparison with the results of multiple regression during the extreme wave conditions, although the statistical parameters of multiple regression and network, both with reduced numbers of inputs, are comparable.

The results of described neural network models with reduced input vector show sufficient improvement in comparison with the results of multiple regression during the extreme wave conditions.

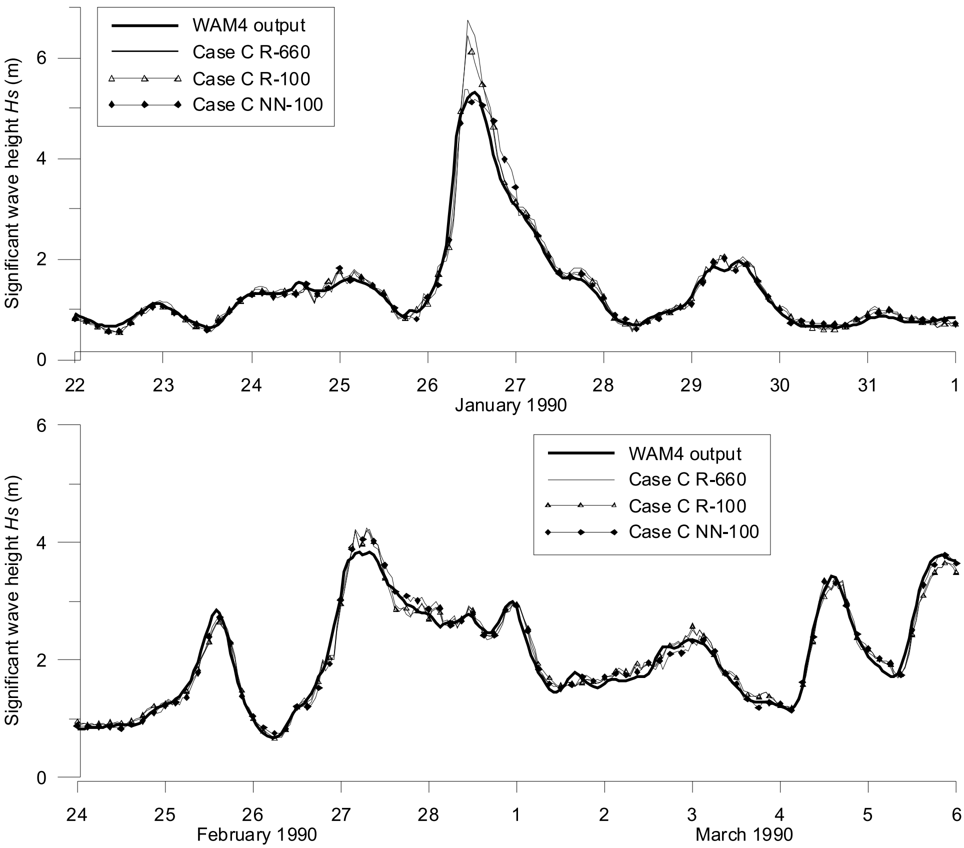


Fig. 11. Case C: 4-hour forecast of significant wave heights for two stormy periods obtained with the different methods

Table 2. Statistical comparison between 4-hour forecast results and the testing data set. Neural network models are indicated as NN-number of inputs; multiple regression results as R-number of inputs. In brackets the values of RMSE and CC obtained in the training process are shown

Number of the testing samples: ~2000		bias (m)	MinE (m)	MaxE (m)	RMSE (m)	SI	CC
Case A	R-330	0.023	–1.579	1.427	0.196	0.148	0.975
	R-47	0.019	–1.024	1.173	0.187	0.141	0.977
	NN-47	**–0.001**	**–0.429**	1.051	0.119 (0.095)	0.090	0.991 (0.990)
Case B	R-330	0.031	–1.844	0.819	0.169	0.126	0.983
	R–147	0.031	–1.836	0.823	0.169	0.128	0.983
	NN-147	–0.010	–0.617	0.796	0.120 (0.082)	0.090	0.991 (0.993)
Case C	R-660	0.010	–1.550	0.926	0.133	0.098	0.988
	R-100	0.006	–1.256	0.992	0.128	0.096	0.989
	NN-100	–0.004	–0.744	**0.594**	**0.109** (0.079)	**0.083**	**0.992** (0.993)

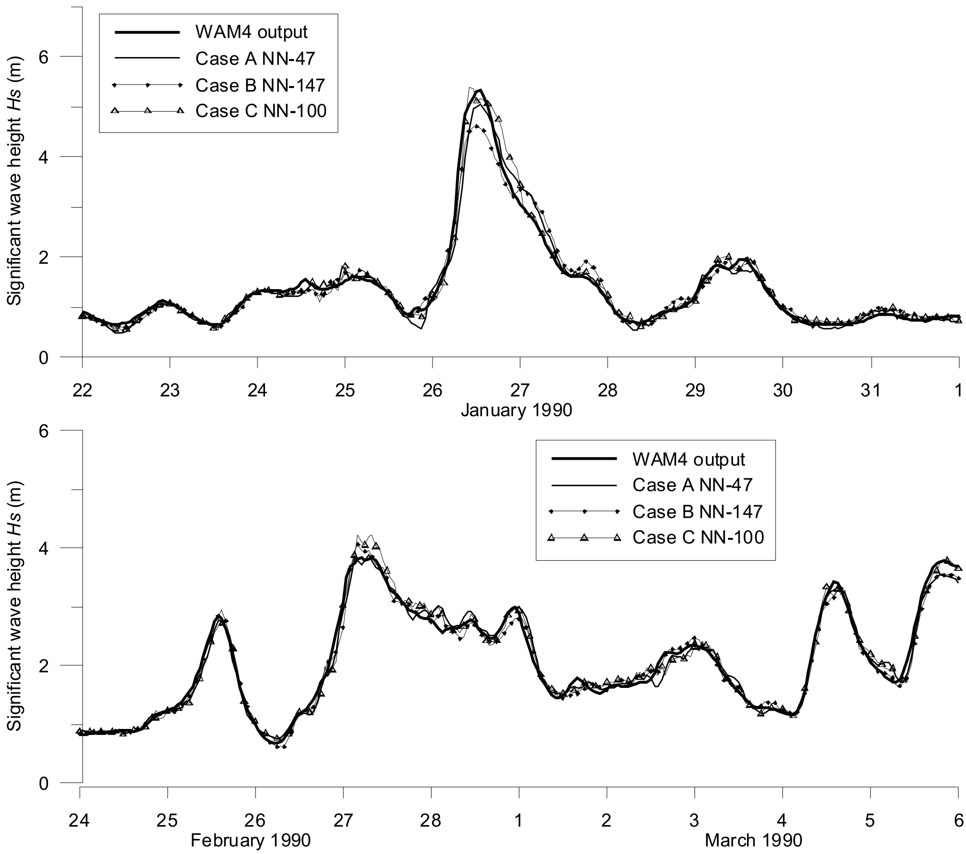


Fig. 12. Comparison of the results of the best networks for the three cases A, B, C

5. Conclusions

In this study, the neural network technique was applied to forecast the significant wave height at a selected location on the Baltic Sea. Significant wave height was modelled at a selected point based on wave and/or wind data from 10 scattered points on the Baltic Sea. The data set for training and testing purposes consisted of high quality hindcast data: wave data from the WAM4 model and atmospheric data from the REMO model.

The wave prediction method is comprised of the following stages:

- formulation of prediction cases,
- application of a linear multiple regression method,
- performance of sensitivity analyses and reduction of input vector,
- construction and application of a neural network model.

The results show that for all the cases the prediction obtained by the neural network conforms very well with testing data.

Detailed analysis indicates that when the WAM4 model data are replaced by real measurements from a number of buoys, the artificial neural network will be able to forecast real significant wave height at selected points on the Baltic Sea. Other parameters such as wave period and direction could easily be modelled in the same manner. A trained network is easy to apply with an 8-hour prediction taking only a few minutes of computation time. This permits forecasts to be updated as data are gathered. Therefore, the proposed neural network method is an efficient tool for locally conducted and short-term forecasts.

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