Forecast of storm surge by means of artificial neural network

Marzena Sztobryn

Instytut Meteorologii i Gospodarki Wodnej, Oddział Morski, ul. Waszyngtona 42, 81-342 Gdynia, Poland

Received 21 January 2002; accepted 28 July 2002

Abstract

This study describes the construction and verification of a model of sea level changes during a storm surge, applying artificial neural network (ANN) methodology in hydrological forecasting in a tideless sea where the variation of water level is only wind generated. Some neural networks were tested to create the forecast model. The results of ANN were compared with observed sea-level values, and with the forecasts calculated by different routine methods. The results of verification show that the neural network methodology could be successfully applied in the routine, operational forecast service.

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Keywords: Sea-level forecast; Artificial neural network; Baltic Sea

1. Introduction

At the south-eastern coast of the Baltic Sea the tides are negligible. Nevertheless, the water level there can vary, as for instance at the water gauge Swinoujscie, from 169 cm above to 134 cm below the mean sea level (set for convenience, to 500 cm). These changes are generated mostly by the impact of the wind field on the surface water. They modify the instantaneous mean sea level, which however, also depends strongly on the bathymetry and the coast line configuration. Forecasts of sea-level changes, and especially storm surge warnings, are prepared to ensure the protection of the coasts and the security of port activities and the coastal navigation.

A storm surge along the Polish coast is, by definition, a rise of the sea level, by at least 70 cm above the mean value. The Maritime Branch of the IMGW (Institute of Meteorology and Water Management) in Gdynia is responsible for the sea-level forecast and storm surge warnings for Polish coastal waters. Some mathematical models used for forecasting purposes, implemented into routine forecasting up to 1997 resulted in better forecast accuracy (higher number of forecasts with less error). Regrettably, all of them are less accurate in the high sea-level intervals than around the average values. Therefore a necessity arose to examine the advantages and abilities inherent in the artificial neural networks (ANN method), in order to include this tool into the storm surge forecasting service.

Such attempts were already made in the Netherlands to forecast the currents in the fairway of the IJchannel (Wust and Noort, 1994), but none of numerical models used there could satisfy the implementation conditions. Another ANN hydrological forecasting model was constructed also in the Netherlands for the complicated basin of the IJsselmeer (Van den Boogaard et al., 1998). This model enables...
calculation of water level forecasts, taking into account all hydrological and meteorological conditions in this complicated water system. Verification of forecasts generated by this model proved applying the ANN methods advantageous in water level prediction. In Bundesamt fuer Seeschiffahrt und Hydrographie (BSH) in Germany, a new ANN method for sea-level prediction along the German North Sea coast was applied as well (Röhrke, 1997). Accuracy of this new model within the interval of high tide anomalies was higher than the accuracy attained by the models used so far in the routine forecasting service and reduced their average error.

2. Artificial Neural Networks

The simplest artificial neural network (ANN), inspired by the brain biology, is the model of a single neuron. This model assumes that, inside a neuron, a transformation of input data vector (i.e. output from the preceding layer) occurs, being an aggregation of input data values, duly weighted (Fig. 1). This transformation is affected by a non-linear activation function. The neurons, joining into the layers and across the layers, create the architecture of ANN. In order to calibrate the model one has to (a) select an optimum architecture of the neural network, i.e. determine the number of layers and number of neurons in each of the layers, (b) find the methods of training, i.e. a method of reducing the error between the expected and obtained value, the latter being calculated in successive steps and (c) calibrate it also indirectly, i.e. depending upon the data structure and the dimensions of the input vector.

The forecast ANN methods need three independent series of input data: a training series, a validation series and a testing series. The first two serve to calibrate the network, the last one-to carry out the verification, i.e. to compare the calculated output data (forecast) with the actual ones. When developing a forecasting ANN model selection of the input data and their structure is the most difficult problem. The freedom of choice of the input data, which is one of basic advantages of neural network, can be more of a hindrance than help when too abundant data sets are prepared or when the data prove improper (Tadeusiewicz, 1993; Herz et al., 1996). The improper data have either no influence on the output variables or on those that are interdependent. The determination of a proper data set, also called the reduction of dimension of input data vector, becomes the primary, and often the most important function in the model calibration.

Fig. 1. Model of neuron body.
3. Construction of the model

In this paper, the input data vector (Fig. 1) was defined as the set of hydrological and meteorological parameters which generate (or influence) the sea-level at a specific moment. In the ‘STATISTICA Neural Network’ software (Statistica NN, 1998), which was used in the investigation, this is called the ‘one case’. The calibration of the model, however, is usually done by a set of all accessible cases. To find the optimum method, the behaviour of the prognostic model was examined and further the quality of the model performance was evaluated when different training methods and different types of the network architecture were applied.

Four models were tested: networks with Radial Basis Function RBF (experiments 1 and 2) with 22 hidden neurons, Generalized Regression Neural Networks GRNN (experiment 2), where the number of neurons is defined by the method, Multilayer Perceptrons with 3 layers MLP3 (experiments 1 and 2) with 2–6 neurons in hidden layer, and Multilayer Perceptrons with 4 layers MLP4 (experiment 1) with 8 neurons in the first hidden layer and 7 neurons in the second hidden layer.

To compare the quality of performance and reliability of forecast, the statistical indicators were applied, calculated for each of the three time series separately: root mean square error (RMS) and correlation coefficient R (standard Pearson correlation coefficient with \( p = 0.92 \) confidence interval). Interrelations between the training and validation series indicators allow us to estimate whether the examined network is able to yield proper performance of the investigated process, and whether it tends to become overlearned or generalised.

4. Verification of the ANN model

The forecasting model was constructed according to the described ANN directions. Only the routinely accessible input data were accepted to the model. To construct the model two different approaches were applied and two separate data sets were used.

The first comprised a continuous data series from March 1997 to August 1997 (experiment 1), the values were taken every 3 hours, so that a full range of sea level values from this long period was contained in the series. The other data set (experiment 2) consisted only of storm-surge situations—over 150 events—observed along the Polish coast between 1950 and 1990, so that only high water levels (above 560 cm) were considered.

The verification of the constructed models was conducted on the data from the westernmost Polish water-gauge Swinoujscie. Meteorological data were taken from the SYNOP messages covering Poland, the Baltic Sea and part of the North Atlantic. Prognostic meteorological data (used in the testing series) were taken from the routinely broadcasted mesoscale forecasts.

4.1. Experiment 1: (continuous data series)

In this experiment the simplest possible structure of the input data vector was applied: the daily mean sea-level value from the preceding day, 6 hours forecast of wind speed and direction generating the sea-level changes in the western part of the Polish coastal waters (Sztobryn, 1999).

Using the data from February 1997, one of the most stormy months, the results (actual and forecast sea-level variation) of the routine and the investigated ANN methods were compared with each other and with the observed values (Fig. 2). The correlation coefficients (Table 1) of the results gained by neural network models ranged between 0.80 and 0.82, while the routine methods gave the values between 0.67 to 0.86 (statistically significant). This points to a good performance concerning the sea-level changes. RMS error of the routine forecast varied from 17 to 42 cm, while for the ANN forecast did not exceed 13–14 cm. However, the best routine method of the highest R coefficient had, regrettably, also the highest RMS error. This proves that the accuracy of the ANN models was an improvement. Admittedly, this success was achieved by including into the model a numerically formulated expression, describing the direct impact of the resultant vector of forecast wind on the coastal water areas. Hitherto the influence of the expected direct wind was applied—in a qualitative form—as a correction to the output of the routine sea-level forecasting models. The latter included the forecast wind computed in more dense or sparse grid points over the sea.
The number of input data (equal to dimension of input vector in ANN), indispensable to operational real-time forecast varied in routine methods from 28 to over 10,000, while with the investigated ANN methods during experiment 1, it was, by definition, only 3. Thus, with a much smaller amount of input data the ANN models gave better accuracy of the forecast, which proves its usability as a routine tool in the daily forecasting service.

4.2. Experiment 2: (random stormy sea-level situations)

In this experiment, comprising the data from more than 150 stormy situations randomly scattered in the fifty years 1950–1999, the number and type of data (dimension of the input vector) was not arbitrarily set, only selected and reduced by means of the following manipulations: (1) by applying the standard Holland genetic algorithm, with elitism and roulette selection (Statistica NN, 1998), (2) by calculating the correlation coefficients and (3) by checking the sensitivity of the model to successive input data introduction. The latter was achieved by checking the quality of the performance first with the examined data series, and then without.

The number of input data vectors was thus reduced from over 1400 parameters to merely 4 to 10 parameters. The same neural network models were used for the verification as applied to the continuous data series (MLP3, RBF) and GRNN. To compare the results gained by ANN methods with the actual ones, the data from the storm surge on 11 and 12 April 1997 were used (Fig. 3). In this case, the R value between the forecast and actual sea-level values was low, though statistically significant and ranged for the relevant ANN methods from 0.27 to 0.58 (Table 1), while for the routine methods it ranged from 0.22 to
The RMS values ranged from 13 to 34 cm for the results gained by ANN, and those from the routine models from 10 to 39 cm. Similarly to the results from Experiment 1, the routine method of the highest R coefficient had, regrettably, also the highest RMS error, and the one with the lowest RMS error had also the lowest R value. Two of the ANN methods, namely the RBF and GRNN, overstate slightly the forecast maximum values. From among the two latter ANN methods, the RBF gives higher R coefficients and lower values of RMS, while applying the GRNN network leads to overlearning, i.e. to an excellent performance of the training series, but to a much worse performance of the validating and testing series. This means that this method is unable to generalise the analysed process or phenomenon, i.e. in this case, to satisfactorily forecast the storm surge.

The interpretation of the results gained by the ANN methods is not, however, as explicit as in the case of continuous data series (Experiment 1), because for instance the MLP 3 method, in which the highest correlation and lowest RMS value were obtained, underestimates the value of forecast maximum. The time of the maximum occurrence (the hour) was correctly predicted and this is deemed to be considerable progress compared to the routine methods.

5. Concluding remarks

It can be concluded that better results are achieved when calibration is done using continuous input data series, as in Experiment 1, than on a group of separate, randomly occurring short sets of ‘storm sea-levels’ data, as in experiment 2.

The inferences drawn from the presented investigations are both of singular and of general character:

♦ performance indicators achieved with the ANN methods are comparable or better than those rendered by the routine methods,
♦ from among the tested methods the MLP3 gave the greatest number of correct predictions,
♦ applying the GRNN network leads to overlearning,
♦ better results were achieved when calibration was done using continuous input data series.

<table>
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<tr>
<th>Table 1</th>
<th>Observed and forecast sea level values and validation estimators</th>
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<tr>
<td></td>
<td>sea level values and validation estimators</td>
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<tr>
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<td>sea max [cm]</td>
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<tr>
<td>EXPERIMENT 1</td>
<td>Observed 562 432 497 1</td>
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<tr>
<td></td>
<td>Method 1 558 460 504 0.67 35</td>
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<td>Method 2 573 467 500 0.73 17</td>
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<td>Method 3 571 476 523 0.86 42</td>
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<td>MLP3 542 467 496 0.82 13</td>
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<td>RBF 551 458 493 0.80 13</td>
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<td>MLP4 547 461 494 0.81 14</td>
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<tr>
<td>EXPERIMENT 2</td>
<td>Observed 600 565 580 1</td>
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<tr>
<td></td>
<td>Method 1 575 571 573 0.22 10.3</td>
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<tr>
<td></td>
<td>Method 3 542 541 542 0.48 39.3</td>
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<td></td>
<td>MLP3 581 566 571 0.58 12.7</td>
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<td></td>
<td>RBF 620 548 578 0.27 23.4</td>
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<td></td>
<td>GRNN 650 544 586 0.31 34.1</td>
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Fig. 3. Comparison between observed and forecast sea levels: 11–12 April 1997.
The presented experiments unquestionably prove the ability of the ANN methods to be developed into a tool for the sea-level forecasting service. The simple experiments presented here should be looked at as the first approach in the preparation of more complex ANN systems covering also other sites along the Polish coast.

References
