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6th IAHR Europe Congress
Warsaw Poland 2020

6th IAHR Europe Congress, June 30th – July 2nd, 2020, Warsaw, Poland

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ABSTRACT

Realization and construction of large infrastructure projects in Germany is governed by a strict legislation for the environmental impact assessment. After the formal approval of a project, a preservation of evidence based on measurements is often required. The objective of this case study is to investigate the proposed deepening of a seaport access channel in the Weser estuary with respect to its impact on hydrodynamics. With the aid of machine learning, regression corresponding parameters are successfully approximated to promote the preservation of evidence. By this application we can obtain insights into the driving physical processes based on neural networks, but still struggle to differentiate between natural variability and the effects of the deepening.

1. Introduction

The Weser estuary stretches from the tidal barrage with freshwater influence in Bremen, Germany, over 120 km into the south-eastern North Sea. The approach channel has been deepened in the past several times in order to allow larger vessels to reach the seaports of Bremerhaven and Bremen. These deepenings had an impact on hydrodynamics, e.g. the tidal range has increased and salt intrudes further upstream (Lange et al., 2008). Therefore it is crucial to properly assess the effects of the currently planned deepening. For the Environmental Impact Assessment, hydro-numerical models have been used to quantify changes of hydrodynamics and salt transport. One aspect of the preservation of evidence is a comparison of the findings of the numerical models with measurements of e.g. water-levels. As water-level measurements in coastal areas are influenced by a number of different processes (e.g. tides, river discharge) on different time-scales (daily to interannual), a functional relationships is needed to relate observed water-level data and relevant processes as forcing parameters. Niemeyer (1995) chose a multiple linear-regression approach, which is in itself limited by the necessity to prescribe a selected number of physical processes. His approach was shown to have a limited accuracy in reproducing observed water values (Lange, 2010). The case study presented here is based on a machine learning strategy applying multidimensional regression, supported by the knowledge of underlying physical processes, which can promote a more precise reproduction of water-levels and thus be applicable as method for a preservation of evidence.

2. Study methods and data

The basic approach in order to determine project related changes in hydrodynamic parameters, here water-levels, is to obtain long-term measurements before and after the project. Without any further influence, the water-level difference between before and after the project would be the sought impact. Unfortunately, water-levels are influenced by a number of environmental parameters such as river discharge, tides and meteorological conditions. In order to account for the different processes a neural network is trained with independent forcing parameters in order to reproduce water levels before the deepening and then used to simulate the non-perturbed state without the deepening. This approach is sketched in Fig. 1.

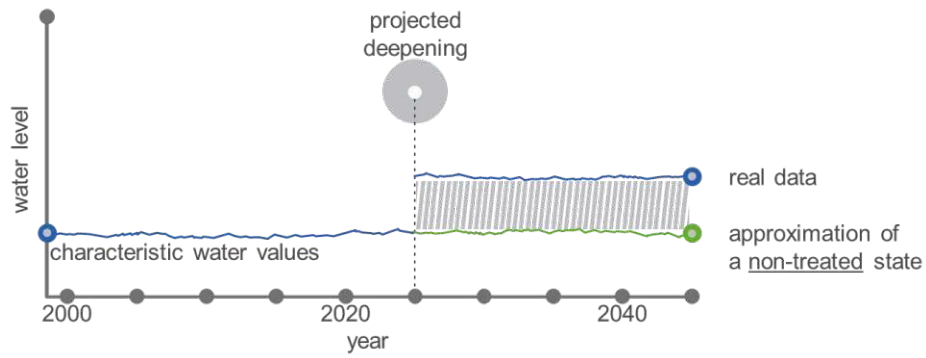

Fig. 1. Idea for a quantitative determination of the project-related impact (shaded grey) of a hydrodynamic parameter (blue) on the basis of neural network-approximated data of a non-deepened state of the Weser River (green).

Within the Weser estuary water-levels are measured at 12 tide gauges, based on these time-series tidal characteristic values (e.g. tidal mean water, tidal low and high water) have been determined. Moreover, river discharge is taken into account. The discharge ranges from 60-3500 $m^3 s^{-1}$ with most frequent values between 100-200 $m^3 s^{-1}$ (Lange et al., 2008). As meteorological forcing measured wind speed and direction from the Outer Weser is considered.

We examined the tidal low and high water at 11 gauges by planning, execution, calculation and interpretation of neural networks using the following 7 forcing parameters: tidal low, mean and high water at the outer Weser Estuary (station “Alte Weser”), the river discharge and meteorological conditions. 100 neural networks are set-up for each of the 11 tide gauges and two observations (tidal low water, tidal high water).For processing we applied the Mathworks machine- and deep learning toolbox, using a 7-105-15-1 fitnet-topology with a feed-forward back-propagation (Levenberg-Marquardt) as learning method and a tangent sigmoid activation function. To compare the neural network performance, quality criteria like the Root-Mean Square Error (RMSE), the relative Mean-Absolute Error (rMAE) and the Error Index (EI) are calculated.

3. Preliminary results

Our machine learning approach is carried out with parameters given above and the two observations tidal low and high water. The deviation between training output and observations is reduced with each iteration until the training is terminated. The training abortion is dependent on the network settings, here chosen as the first minimum of the validation error. Such abortion criteria are necessary to maintain the generalization ability and applicability of a neural network to new data. Due to such a termination criterion, the training output may not be 100% consistent with observations. As a result we obtain machine-learning data of the characteristic tidal values which can be compared to the observations. Through analyzing the quality criteria, ⅔ of the 2200 neural networks could reproduce the observations to a satisfying degree. For example, on average the obtained RSME for best ⅔ neural networks at one station (gauge Vegesack) is 7.5 cm, taking the spread of 514-1016 cm for the corresponding values of tidal high water into account. Each of the about 1450 individual neural networks of all stations map the functional relationships between the forcing parameters and the observations with a deviation of about 2-10 cm. Further, we evaluated the impact of different forcing parameters based on the weighting of the neural networks.

Since the conducted training process generates promising results, data of the 7 forcing parameters from another time period can be tested using the same weighted neural networks. Thereby, adding the two observations is no longer necessary, since no weighting adjustment takes place. In this application of re-using the weighted neural networks we find higher variations between the machine-learning data and measurements, which substantiate the challenge to distinguish project-related changes from other natural, anthropogenic or systematic influences.

References

Lange D (2010) Dokumentation und Durchführung der (…) angeordneten Beweissicherungsauflagen und Bewertung der Ergebnisse, Abschlussbericht, Waterways and Shipping Office Bremerhaven, Germany
Lange D, Müller H, Piechotta F, Schubert R (2008) The Weser Estuary, Die Küste, 74 ICCE, 275-287
Niemeyer HD (1995) Ermittlung der Änderungen mittlerer Tidescheitel und -hübe in der Tideelbe infolge des Ausbaus von Außen- und Unterelbe auf KN -13,5m, Kurzfassung, Lower Saxony State Office for Ecology, Germany
Schubert R, Vierfuß U, Schiller U; Brand H (2006) (…) Gutachten zur ausbaubedingten Änderung von Hydrodynamik und Salztransport, BAW-Nr. 5.02.10048.00-1, Federal Waterways Engineering and Research Institute, Germany