

Combining numerical models and computational intelligence techniques in sedimentation prediction

B. Bhattacharya¹, T. van Kessel² and D.P. Solomatine³

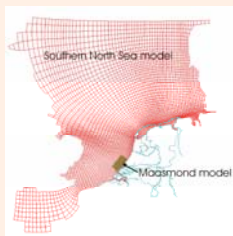
¹ B.Bhattacharya @ unesco-ihe.org, ² Thijs.vanKessel@deltares.nl, & ³ D.Solomatine @ unesco-ihe.org

Abstract

Sediments are important in many aquatic systems. Their transportation and deposition has significant implication on morphology, navigability and water quality. Numerical models are usually employed to assess the impact of individual or combined anthropogenic activities by carrying out multiple scenario computations, sometimes over long simulation periods to predict suspended particulate matter (SPM) concentrations and siltation rates. For studies along the Dutch coast the numerical modelling tool Delft3D has been frequently applied. The numerical models suffer from high computing time.

As an alternative we developed a hybrid modelling approach by combining numerical and data-driven modelling (DDM) to predict SPM concentrations at the Dutch coastal region. An artificial neural network (ANN) model is built using measured data and data generated by a numerical model to predict SPM time series. The ANN model uses bed shear stress (from a numerical model) and measured wave heights and wind speeds and computes SPM. The generated SPM time series is used as a time-varying sediment boundary condition at the open boundary of a fine-grid 3D numerical model of the Dutch Coast using Delft3D. Measured sediment data at the boundary is not available and as a result a fixed sediment boundary condition is normally applied. The numerical model's output (SPM concentrations) with time-invariant and time varying sediment boundary condition is compared. It is concluded that the sediment boundary condition provided by the ANN model provides improved simulation results and the methodology presents new horizons for developing hybrid models.

Numerical modelling



The numerical modelling tool Delft3D (by Deltares) is used to build both an overall model of the Southern North Sea and a local model, called the Maasmond model, that covers the area around the mouth of River Rhine. An overall model is set up to capture the large-scale features of fine sediment transport in the Dutch coastal zone, but lacks sufficient resolution to simulate local details accurately. Therefore, a local model of the Maasmond area is also developed.

Fig.1 The study area.

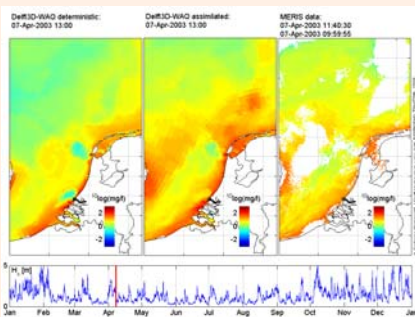


Fig. 2 Observed, computed and assimilated averaged suspended sediment concentration at surface of North Sea on 7 April, 2003

Data-driven modelling

The neural network model is built using the hourly sediment concentration data collected below the water surface at 10 km offshore of Noordwijk. The bed shear stress, south-westerly wind component and significant wave heights are selected as the input variables to the neural network model. The model predicts hourly sediment concentration. The bed shear stress and sediment concentration data are filtered (using moving average over 25 hour) to remove short-term fluctuations mainly due to tides. Before building the model all input data are transformed to have zero mean and unit variance. The sediment concentration predicted by the neural network model is found to be satisfactory.

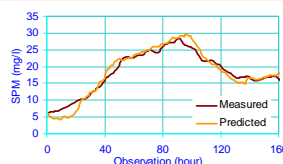


Fig. 3 Comparison of SPM concentration predicted by the neural network model with the measured data during a storm period during 7th September 2001 to 14th September 2001 (about a week)

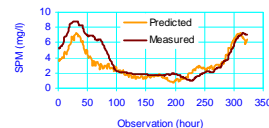


Fig. 4 Comparison of SPM concentration predicted by the neural network model with the measured data during a calm period during 10th February 2001 to 24th February 2001 (about two weeks).

Hybrid modelling: combining numerical & data-driven modelling

The Maasmond model used a spatially-varying but time invariant sediment concentration at the south boundary. At the other two open boundaries, namely the west and the north, the sediment boundary condition is a fixed concentration level. As fine sediments come from the south, the use of a time-invariant sediment boundary condition at the south boundary is debatable. A key research issue in this respect is to investigate the influence of a time-varying sediment boundary condition at the south boundary. The neural network model built with the Noordwijk data is used to generate sediment concentrations for the south boundary.

The neural network model's output was used as the time-varying sediment boundary condition in the Maasmond model. At the observation point nearer to the southern boundary the trends of the predicted sediment concentration time series in both cases are the same, however, for the time-varying sediment boundary condition the amplitude is smaller. At observation points further away from the boundary the difference in the predicted sediment concentration time series is not discernible. This perhaps can be explained by the fact that for short-term simulations the local sediment supply determines the sediment concentrations in the water column. The influence of time-varying sediment boundary concentrations at distances away from the boundary for longer simulation time is still to be investigated.

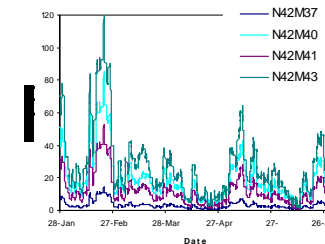


Fig. 5 Sediment boundary conditions generated by ANN.

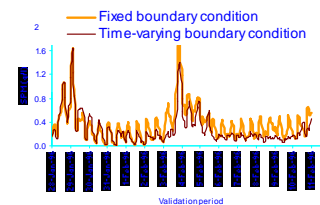


Fig. 6 Comparison of predicted sediment concentrations.

Conclusions

- The research shows some novel techniques of modelling fine sediment transport by combining numerical and data-driven modelling approaches.
- The accuracy of the neural network model in predicting sediment concentration is high and is found to be applicable at different locations.
- The methodology shows a way of using data-driven modelling to provide the boundary condition of a numerical model and thereby, presents a useful way of combining data-driven modelling with numerical modelling.