IUTAM Symposium on Storm Surge Modelling and Forecasting

Combining machine learning with computational hydrodynamics for prediction of tidal surge inundation at estuarine ports

Jon French[a]*, Robert Mawdsley[a], Taku Fujiyama[b], Kamal Achuthan[b]

aCoastal and Estuarine Research Unit, UCL Department of Geography, University College London, Gower Street, London, WC1E 6BT, UK
bUCL Department of Civil Environmental and Geomatic Engineering, University College London, Gower Street, London, WC1E 6BT, UK

Abstract

Accurate forecasts of extreme storm surge water levels are vital for operators of major ports. Existing regional tide-surge models perform well at the open coast but their low spatial resolution makes their forecasts less reliable for ports located in estuaries. In December 2013, a tidal surge in the North Sea with an estimated return period of 760 years partially flooded the Port of Immingham in the Humber estuary, on the UK east coast. Damage to critical infrastructure caused several weeks of disruption to vital supply chains and highlighted a need for additional forecasting tools to supplement national surge warnings. In this paper, we show that Artificial Neural Networks (ANNs) can generate better short-term forecasts of extreme water levels at estuarine ports. Using Immingham as a test case, an ANN is configured to simulate the tidal surge residual using an input vector that includes observations of surge at distant tide gauges in NW Scotland, wind and atmospheric pressure, and the predicted astronomical tide at Immingham. The forecast surge time-series, combined with the astronomical tide, provides a boundary condition for a local high-resolution 2D hydrodynamic model that predicts flood extent and damage potential across the port. Although the forecasting horizon of the ANN is limited, 6 to 24 hour forecasts at Immingham achieve an accuracy comparable to or better than the UK national tide-surge model and at far less computational cost. Use of a local rather than a larger regional hydrodynamic model means that potential inundation can be simulated very rapidly at high spatial resolution. Validation against the 2013 surge shows that the hybrid ANN-hydrodynamic model generates realistic flood extents that can inform port resilience planning.

* Corresponding author. Tel.: +44 20 7679 0580; fax: +44 20 7679 0565.
   E-mail address: j.french@ucl.ac.uk

1. Introduction

Effective prediction of tidal storm surges is important for the operators of major ports since their infrastructure is necessarily located close to sea level. Inundation of port facilities can damage critical elements of this infrastructure, significantly disrupt port operations and cause downstream impacts on supply chains. The risk of inundation by storm surge is typically estimated from peak water levels computed from extreme value analysis of historic records[1,2]. Short-term forecasts of individual flood events are delivered by regional ocean models, forced by tidal and meteorological inputs, which predict the space-time evolution of the surge component of water level[3]. However, extreme value analysis is sensitive to the assumptions made[2], and provides no information on spatial variation in flood extent, depth and duration in large port facilities. Also, whilst regional tide-surge models perform well at the open coast, their low spatial resolution (typically 1 to 10 km) limits forecast accuracy for ports located in estuaries.

As part of a NERC Environmental Risks to Infrastructure Innovation Programme project, we are investigating methods for the generation of better storm surge forecasts to inform resilience planning by operators of the major North Sea ports along the UK east coast (Fig. 1a). Of particular importance is the Port of Immingham in the Humber estuary. Immingham is the largest bulk cargo port in the UK and handles flows of coal and biomass that are important for power generation. The North Sea tidal surge of December 2013 was larger at Immingham than that of the historic storm of 1953, with an estimated return period of 760 years (Fig. 1b). The 2013 event partly flooded the port, causing damage to port and rail transport infrastructure and disrupting operations for several weeks.
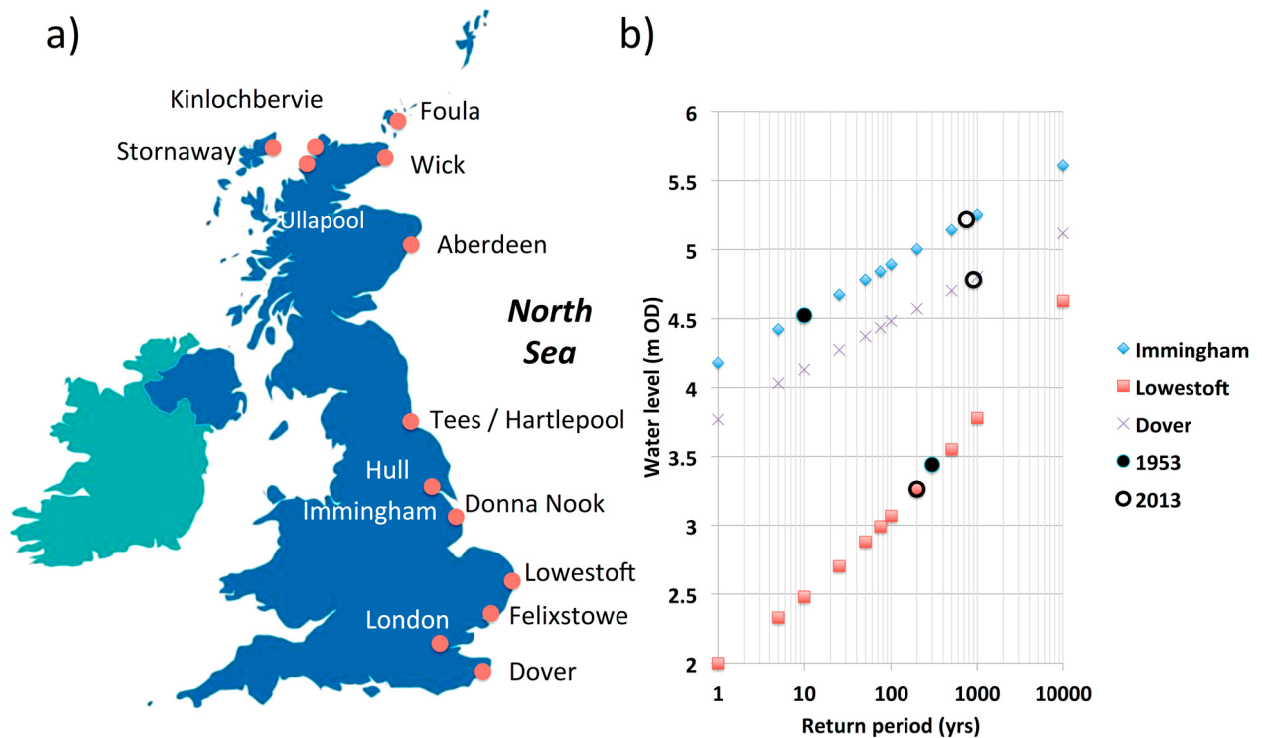

Fig. 1. (a) Location of Port of Immingham, UK, and of observation locations used in the generation of ANN input vectors; (b) recurrence intervals for extreme water levels[1] for selected North Sea ports, including January 1953 and December 2013 storm surge events.

In this paper, we present a hybrid approach to storm surge forecasting and modelling that combines machine learning with computational hydrodynamic modelling. A data-driven Artificial Neural Network (ANN) is used to

forecast the surge component of water level at a port of interest based on the observed far-field tidal surge, regional meteorological observations and the predicted astronomical tide. The forecast surge is combined with the predicted tide to generate a total water level series with which to force a numerical hydrodynamic model of inundation within the port. The ANN-generated local water-level boundary condition allows simulation of inundation at a high spatial resolution without the need for a larger coastal shelf model. This hybrid surge forecasting and modelling system can be run almost in real-time as a cost-effective supplement to existing national storm surge warnings and forecasts.

2. Approach

2.1. Artificial Neural Network implementation

An Artificial Neural Network (ANN) is a massively parallel computational architecture that is inspired by and shares some of the operational characteristics of biological neural networks within the human brain[4]. Of particular importance for our problem are networks designed for supervised training in which relationships between a data and a parameter domain are learned given sufficient training data. Specifically, we use a feed-forward network architecture (Fig. 2a) in combination with an error back-propagation algorithm[5] to discern complex non-linear mappings between time-series for a set of metocean variables that contain useful information (the input vector or 'layer') and a target time-series of the surge component of water level at the location of interest (the 'output layer').

The goal of the ANN[6] is to generalize a relationship of the form

$$Y_m = f(X_n) \tag{1}$$

where X is an n-dimensional input vector consisting of variables $x_1, ..., x_i, ..., x_n$; and Y is vector consisting of the target variables of interest $y_1, ..., y_i, ..., y_m$ (in our case, $m = 1$ as we have only a single target, the surge residual at the port of interest). Each neuron (Fig. 2b) operates according to an activation function given, for the jth node, by

$$y_j = f(X \cdot W_j + b_j) \tag{2}$$

where W_j is the vector of input weights and b_j a bias weight for node j. There are various options for the choice of the activation function, f in (2). One of the more widely used is the log-sigmoid function, a bounded, monotonic, nondecreasing function that provides a smooth nonlinear output response.

A supervised ANN makes use of a suitably large set of paired input and output data values to guide a training process that finds an optimal set of weights and biases. Selection of suitable inputs must be guided by fundamental understanding of the system being modelled but also involves considerable trial and error. Other studies have demonstrated the potential of ANN to predict and forecast tidal and surge water levels when driven by observations from nearby tide gauges and metocean data such as atmospheric pressure and wind stress[e.g. 7,8]. In the case of the North Sea, surges typically evolve along a southerly track and it seems reasonable to expect that we should see useful information contained in prior observations at tide gauges in NW Scotland (Fig. 1a) as well as wind and pressure fields. Surge-tide interaction is important in the North Sea and so the predicted astronomical tide is also a relevant input variable. The predictive value of the far-field 'external' surge is demonstrated by Fig. 3, which shows that the observed tidal surge residuals at Stornoway, Kinlochbervie and Ullapool (Fig. 1a) exhibit a maximum correlation with the surge at Immingham at a lag of about -18 to -24 hours. Trial and error sensitivity analysis resulted in a final input vector that included the observed surge at Kinlochbervie, together with the wind stress and atmospheric pressure at Foula and (more locally) Donna Nook, and the predicted tide at Immingham. Preceding observations of the surge residual at Immingham were also included to capture the occurrence of larger negative surges that are often seen to precede the larger positive surges. Inputs were subject to a range of lags to generate 6, 12, 18 and 24-hour forecasts of the surge residual at Immingham.

ANN models were implemented using routines in the Matlab Neural Network Toolbox (Matlab release R16a; www.mathworks.com). The input vector was normalized from 0 to 1 and divided into training, validation and test datasets in the ratio 70:15:15. A log-sigmoid function was used between the input and hidden layers and a linear

function between the hidden and output layers. We use a single hidden layer with a number of neurons guided by the size of the problem (number of inputs and observations available for training) and the need to avoid over-fitting.
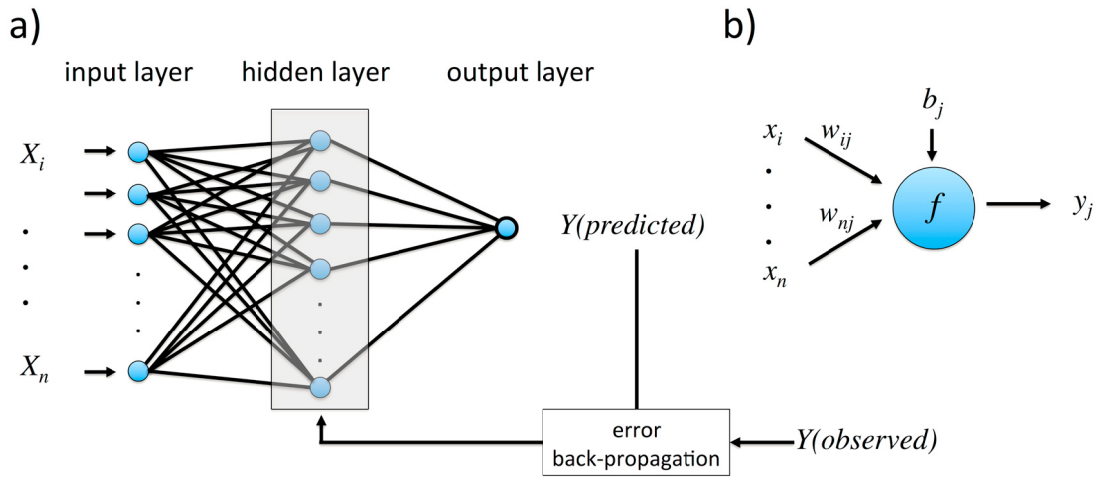

Fig. 2. (a) Definition sketch of feed-forward network architecture with error back-propagation; (b) configuration of weighted inputs and bias for a node within the hidden layer.
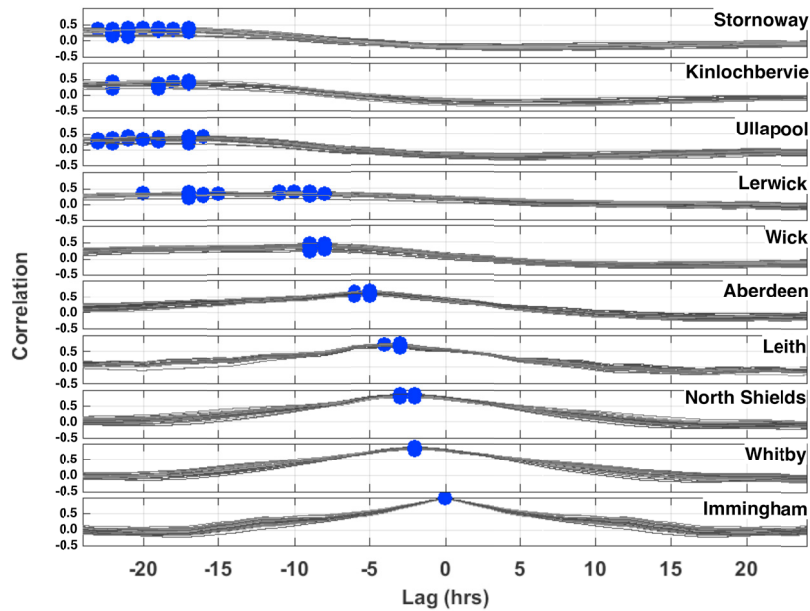

Fig. 3. Correlograms showing the lagged correlation between tidal surge residual for various tide gauges and Immingham. Analysis is performed for each year of data available (post-1950s). Dots show lag at which peak correlation occurs in each year. Of significance here are the -18 to -24 hour lags for tide gauges in NW Scotland (Stornoway, Kinlochbervie, Ullapool).

2.2. Hydrodynamic model implementation

Hydrodynamic computations of surge inundation within the port were performed using the open source Telemac-2D code (www.open-telemac.org). Telemac-2D[9] solves the depth-averaged 2D shallow water equations given by

$$\frac{\partial h}{\partial t} + \vec{u} \cdot \overrightarrow{\mathbf{grad}}(h) + h \operatorname{div}\left(\vec{u}\right) = 0 \tag{3}$$

$$\frac{\partial u}{\partial t} + \vec{u} \cdot \overrightarrow{\mathbf{grad}}(u) = -g \frac{\partial Z}{\partial x} + F_x + \frac{1}{h} \operatorname{div}\left(h v_T \overrightarrow{\mathbf{grad}}\, u\right) \tag{4}$$

$$\frac{\partial v}{\partial t} + \vec{u} \cdot \overrightarrow{\mathbf{grad}}(v) = -g \frac{\partial Z}{\partial y} + F_y + \frac{1}{h} \operatorname{div}\left(h v_T \overrightarrow{\mathbf{grad}}\, v\right) \tag{5}$$

where u and v are the flow velocity in x and y directions, h is water depth, Z the free surface elevation, and t time. F_x and F_y are source terms to represent boundary friction, v_T is an eddy viscosity and g is the gravitational acceleration.

Equations (3) - (5) are solved using a finite element discretization on an unstructured triangular mesh. The model domain covers the entire frontage of the port and extends landward to include the topography of the enclosing flood compartment. The minimum element size is about 2 m, sufficient to resolve the larger structures within the port. Terrain was modelled using airborne lidar data (0.25 to 2 m horizontal interval). Preliminary Telemac-2D runs for the surge of December 2013 are presented here. These were run in parallel using 16 cores on a single compute node.

3. Results

3.1. ANN performance

Trial and error experimentation showed that a hidden layer size of 30 neurons was adequate to give a good performance, without excessive training times or any evidence of over fitting (Fig 4a). The overall fit is good (e.g. Fig. 4b), although there is a slight bias towards under-prediction at the upper end of the surge sample.
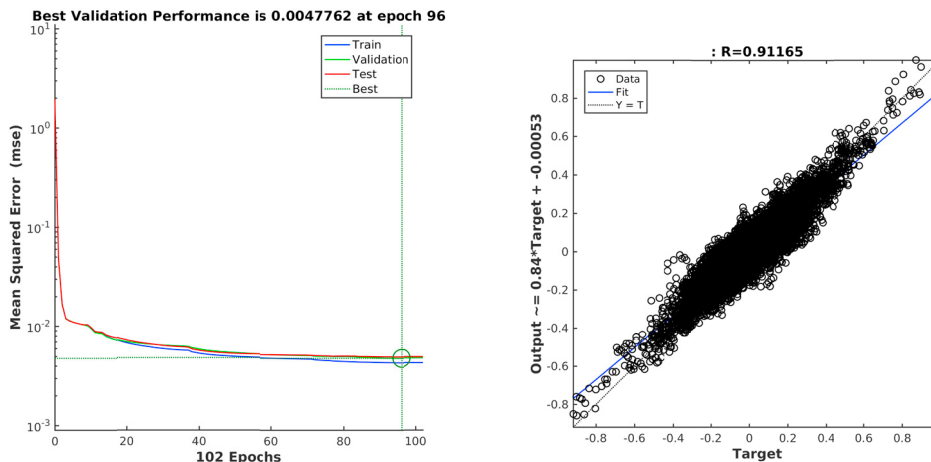

Fig. 4. Illustrative ANN training (a) and performance (b) for a 12 hour surge residual forecast. This simulation uses training data for 2010 and a hidden layer of 30 neurons.

It is interesting to compare the performance of a simple ANN with the forecast accuracy of the UK national CS3 numerical tide-surge model. Only 6-hour archived forecasts for the CS3 model were available in numerical form. These also show good performance, with less bias but a slightly weaker overall correlation than the ANN (Fig 5.) Table 1 shows a comparison of 6, 12, 18 and 24 ANN forecasts with the 6-hour CS3 model forecasts. Here it is evident that overall model performance is actually slightly better with the ANN in terms of root–mean square errors (RMSE) and correlations between predicted and observed surge. The two approaches yield rather more similar results for 2013 (which had a relatively high surge variance) than in 2010 (which had fewer large surge events).
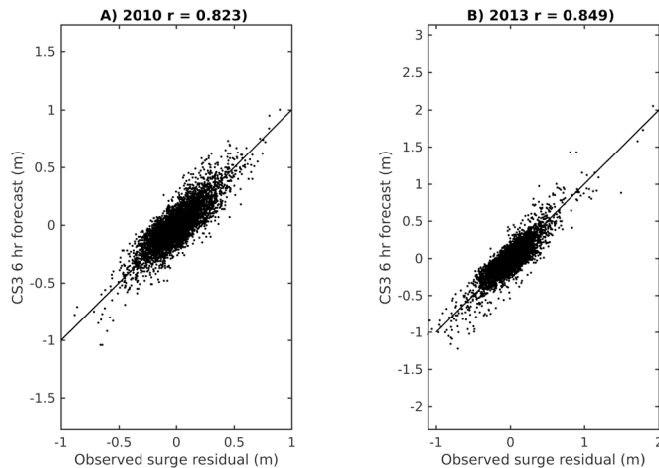

Fig. 5. CS3 numerical tide-surge model performance (6-hour forecast) at Immingham for a) 2010; and b) 2013.

A key test of the surge forecast is its ability to resolve the magnitude and timing of the largest events. Here we focus on the December 2013 surge, which caused damage at Immingham. Fig. 6 shows time-series for the observed December 2013 surge at Immingham, together with the 6-hour CS3 model and the comparable 6-hour ANN model forecasts. Both models resolve the event well in terms of both timing and magnitude, although the CS3 forecast actually over-predicts a little on this occasion. This shows the skill of a relatively simple ANN model at forecasting a major event to an accuracy comparable to that of a more complex numerical tide-surge model.

Table 1. Summary comparison of RMSE and correlation (r) for ANN and CS3 (National Storm Tide Warning Service) surge residual forecasts at the Port of Immingham for select forecasting time windows and two different years.

	ANN model				CS3 model
Data year	6 hr	12 hr	18 hr	24 hr	6 hr
2010 RMSE (m)	0.057	0.063	0.067	0.068	0.091
r	0.937	0.912	0.910	0.907	0.823
2013 RMSE (m)	0.064	0.070	0.077	0.080	0.097
r	0.950	0.941	0.928	0.921	0.849

3.2. Simulated inundation of port facilities

Only an approximate flood extent map, together with qualitative evidence obtained from discussions with the port operators, exists with which to validate the Telemac-2D simulations of surge inundation. However, an initial test simulation of the December 2013 surge (forced by imposition of an ANN-generated forecast of the total water

level at the port entrance) corresponds very well to the indicative actual flood extent polygon (Fig. 7a). The peak water level during this event reached 5.22 m above Ordnance Datum (roughly mean sea-level), of which about 1.6 m was attributable to the instantaneous surge at high water. Maximum flood depths exceeded 1 m in a number of locations, and larger areas of the port were flooded to over 0.5 m. Existing assessments of flood risk and damage potential are typically based on GIS-based extrapolation of single-valued extreme water levels associated with a given return period. Fig. 7b shows how this approach over-estimates overall flood extent and predicts greater inundation depths. Given the sensitivity of infrastructure damage and port operation to depth of inundation, this might trigger costly adaptive measures (e.g. movement of equipment or shipping containers) in some parts of a facility when effort might be better expended elsewhere.
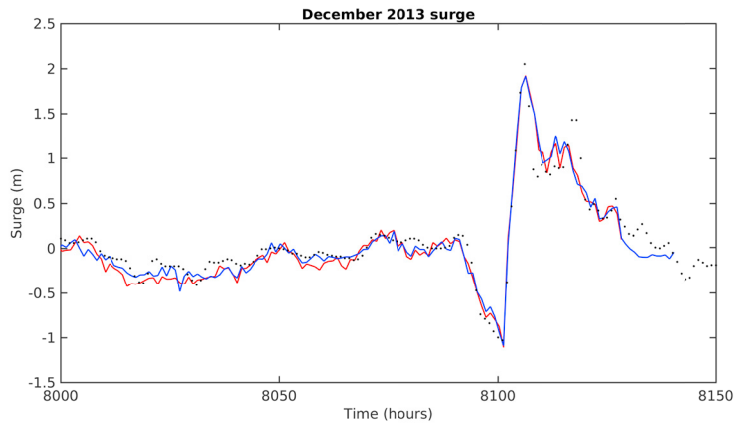

Fig. 6. Observed (red line) surge residual and the 6-hour CS3 numerical model (black dots) and 18 hour ANN model (blue line) forecasts for the December 2013 event at Immingham.
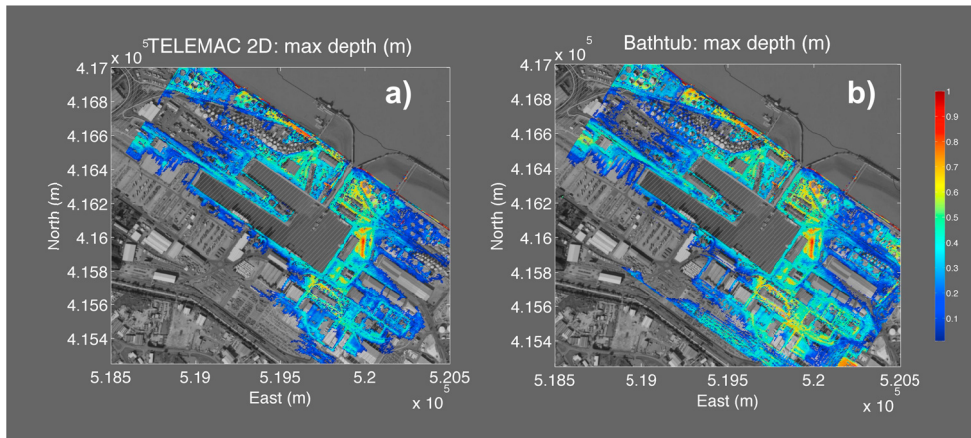

Fig. 7 (a) Illustrative Telemac2D simulation of maximum inundation depths within the port for the December 2013 surge; (b) simple GIS 'bath tub' model in which flood extent is estimated by extrapolation of the maximum water level reached during the surge. Note that the estuary and dock have been masked in both images to highlight the inundation of normally dry areas.

4. Discussion and conclusions

Numerical tide-surge models are necessarily implemented for large areas of coastal shelf, but limited bathymetric resolution, and a relatively coarse mesh resolution, restricts their ability to resolve the propagation of surges within estuaries, where many large ports are located. Our hybrid ANN-computational forecast model demonstrates the ability of an ANN to transfer surge forecast information from a small set of metocean forcing variables, including the observed far-field surge, directly to an estuarine port. While the ANN does not offer the longer-range (24 to 42 hour) forecasting capability of a full numerical tide-surge model, it can be used to provide forecasts within a 12 to 24 hour window that are of comparable or better accuracy.

ANN-generated water level series can then be used as a boundary condition for a local computational hydrodynamic simulation of flood extent, depth, and duration for a forecast event within the port facility. The use of a smaller model domain and focus on a single surge event means that this simulation can be run at a very high spatial resolution. Simulation times of 15 - 20 minutes (or less) are well within the capability of a single multi-core compute node and can be completed 'on demand' if a predicted surge water level exceeds a port-specific threshold.

Work is currently ongoing to further refine the ANN through the extension of the sensitivity analysis to include different combinations of input variables. A key aim here is to eliminate as a far as possible the slight tendency of the initial ANN implementation to under-predict peak water levels. Refinements to the Telemac-2D model include improvements to the mesh to include a more complete representation of structures in conjunction with an improved treatment of buildings and defensive structures and experiments with more sophisticated turbulence and friction parameterizations. We are also progressing towards an operational version of the forecasting system that is able to receive live data feeds and can therefore be used directly by the port operator.

Acknowledgements

References

1. Batstone C, Lawless M, Tawn J, Horsburgh K, Blackman D, McMillan A, Worth D, Leager S, Hunt T. A UK best-practice approach for extreme sea-level analysis along complex topographic coastlines. *Coast Eng* 2013; **71**:28-39.
2. Lopeman C, Geodatis G, Franco G. Extreme storm surge hazard estimation in lower Manhattan. *Nat. Hazards* 2015; **78**:355-91.
3. Flowerdew J, Horsburgh K, Wilson C, Mylne K. Development and evaluation of an ensemble forecasting system for coastal storm surges. Quart J Roy Meteorol Soc 2010; **136**: 1444-56.
4. Haykin S. *Neural networks: A comprehensive foundation*. 2nd. New York: Prentice-Hall; 1998.
5. Rumelhart DE, Hinton GE, Williams RJ. Learning representations by back-propagating errors. *Nature* 1986; **323**:533-6.
6. ASCE Task Committee. Artificial neural networks in hydrology. I: preliminary concepts. *J Hydrologic Eng* 2000; **5**:115-23.
7. Sztorbryn. M. Forecast of storm surge by means of artificial neural network. *Neth J Sea Res* 2003; **49**:317-22.
8. Nitsure SP, Londhe SN, Khare KC. Prediction of sea water levels using wind information and soft computing techniques. *Appl. Ocean Eng* 2014; **46**:344-51.
9. Hervouet J-M. *Hydrodynamics of free surface flows: modelling with the finite element method*. Chichester: John Wiley & Sons; 2007.