Urban flood prediction in real-time from weather radar and rainfall data using artificial neural networks

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Abstract This paper describes the application of Artificial Neural Networks (ANNs) as Data Driven Models (DDMs) to predict urban flooding in real-time based on weather radar and/or raingauge rainfall data. A 123-manhole combined sewer sub-network from Keighley, West Yorkshire, UK is used to demonstrate the methodology. An ANN is configured for prediction of flooding at manholes based on rainfall input. In the absence of actual flood data, the 3DNet / SIPSON simulator, which uses a conventional hydrodynamic approach to predict flooding surcharge levels in sewer networks, is employed to provide the target data for training the ANN. The ANN model, once trained, acts as a rapid surrogate for the hydrodynamic simulator. Artificial rainfall profiles derived from observed data provide the input. Both flood-level analogue and flood-severity classification schemes are implemented. We also investigate the use of an ANN for nowcasting of rainfall based on the relationship between radar data and recorded rainfall history. This allows the two ANNs to be cascaded to predict flooding in real-time based on weather radar.

Key words artificial neural network; manhole; multi-layer perceptron; nowcasting; prediction; rainfall; urban flood; weather radar

BACKGROUND

Recent studies (Min *et al.*, 2011; Pall *et al.*, 2011) have documented the increased frequency and likelihood of extreme precipitation events. At the same time, the complete redesign and construction of urban drainage networks to prevent flooding during such events in every case would be prohibitively expensive with increasing urbanisation further exacerbating this problem. Therefore models are required, which can provide predictions of location, severity and/or risk of flooding. In order to be operationally useful, these need to provide at least a 2-hour lead-time (Einfalt *et al.*, 2004).

Conventional hydraulic simulators have been used to model the response of Urban Drainage Networks (UDNs) to rainfall events. However, for large networks, these can be slow and computationally expensive. A faster surrogate method is sought, which would permit modelling of very large networks in real-time, without unacceptable degradation of accuracy. Also, in the worst case, the predictive ability of such models is limited by the "time of entry" for the sewer network, with the possibility of flooding commencing from this time onwards, following the start of precipitation. In practice, this would normally be of the order of minutes, rather than hours.

Therefore prediction of rainfall is a requirement to achieve lead-times sought. Many papers have been written on rainfall nowcasting methods from radar rainfall images (Schellart *et al.*, 2009; Wang *et al.*, 2009). In this study, rainfall intensity predictions are made for a 3 × 3 km catchment, using Met Office Nimrod UK-1km composite radar images with 5-minute temporal resolution.

As part of University of Exeter's research under Work Package 3.6 of the Flood Risk Management Research Consortium Phase 2 (FRMRC2) Project, we developed the 'RAdar Pluvial flooding Identification for Drainage System' (RAPIDS) using ANN's to predict flooding in sewer systems. The RAPIDS project includes two phases: RAPIDS1, which addresses the need for a faster surrogate for hydraulic simulators, and RAPIDS2, which provides nowcasting for rainfall over the catchment containing the modelled UDN. It is hoped to be able to demonstrate the cascading of these two systems to provide the required urban flood predictive model.

METHODOLOGY

RAPIDS1

The ANN framework is based on a 2-layer, feedforward MLP (Multi-Layer Perceptron), used to relate incoming rainstorm data to the extent of flooding present at each manhole in the UDN. It has

the same number of output neurons as manholes. The number of neurons in the hidden layer and number of input nodes are varied to establish an optimum. The supervised training regime uses a backpropagation of error quasi-Newton gradient-descent method. A moving time-window approach is implemented whereby three time-series traces (rainfall intensity, cumulative rainfall and elapsed time) are provided as inputs to the ANN. The number of input nodes is therefore three times the number of 3-minute time-steps in the input time-window (e.g. for a 30-minute input time window, 30 input nodes are used). Output target signals for training and evaluation of ANN performance are provided from the flood-level hydrographs generated by the SIPSON (University of Belgrade, 2010) hydrodynamic simulator outputs for each manhole. The trained ANN thus aims to generate the same hydrographs, based on learning the relationship between the provided input signals and the SIPSON-generated targets. Figure 1(a) illustrates the architecture of the ANN system to predict SIPSON outputs. The target signals selected are the flood levels at each manhole at a time-step that corresponds to the desired prediction lead-time (i.e. up to 60 minutes). Storm profile data arrays of the three input-signals are prepared for use as the time-series input to the ANN as illustrated in Fig. 1(b). Input data are normalised.

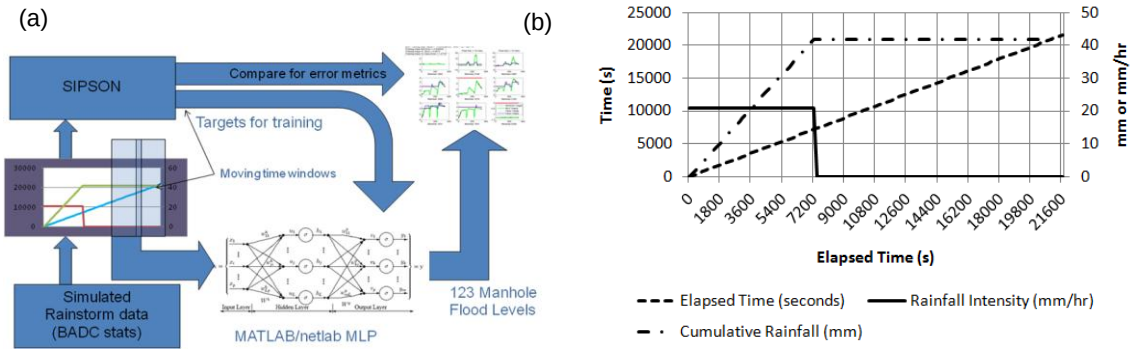

Fig. 1 (a) Architecture of RAPIDS1 (b) ANN Input signals for a typical design storm.

A constant 6-h simulated period for each rainstorm is used throughout, with design storms of 0.5, 1, 2 and 3-h duration and return periods of 1, 10, 50 and 100 years. A sampling period of 3-minutes applies in all cases.

RAPIDS2

Treatment of radar rainfall images directly by an ANN is still computationally prohibitive since, for example, for a 3-h prediction there would be 36-images, each with at least 360^2-pixels (allowing for a maximum storm velocity of 60 km/h). This would potentially require ~5×10^6 neurons (at 1-neuron per pixel). Therefore features are extracted from the rain echoes in each time-step and associated with features from the previous time-step using a 1-nearest neighbour approach. These can then be applied to the inputs of an ANN as time-series signals.

Rain echoes are first distinguished and labelled by thresholding the image, smoothing and pre-filtering to remove clutter. A low threshold (e.g. 0.25 mm/h) is used to ensure rejected rainfall has very low probability of contributing to flooding. Features extracted for each echo include: positions of geometric centroid and centre of rainmass, area, total rainmass, north, south, east and west extremities and peak intensity. It is proposed to use principal component analysis to rank these features in terms of predictive skill.

The same time-windowed ANN framework as for RAPIDS1 can then be implemented. Target rainfall for training and evaluating the ANN is derived from the individual rainfall intensities for the radar image pixels covering the required catchment containing the UDN to be modelled.

The final stage of the RAPIDS project will be to cascade the two stages together, RAPIDS2 providing predicted rainfall, which can be applied to RAPIDS1 inputs to provide flood-severity predictions for each manhole in the UDN.

CASE STUDY

An ANN with 123-outputs is used to model the Stockbridge sub-section of the combined rain/wastewater drainage system for the town of Keighley, West Yorkshire, UK (Fig. 2), containing 123 manholes and one combined sewer overflow. This implements a surrogate DDM for the 3DNet / SIPSON simulator, by using its output hydrographs as target data for training the ANN. The neural network will output a floating-point estimate of the level of flooding at each manhole. However, this level of accuracy is unlikely to be required for flood-warnings. Therefore we use a classification scheme for flood severity shown in Table 1. This is used by a wrapper function around the ANN to convert flood levels to classes. The flood classification threshold edges are deliberately nonlinear to demonstrate flexibility of the approach.

A full 16-storm, leave-one-out cross validation (LOOCV standard method) (Cawley & Talbot, 2003) is conducted, using each of the 16 design storms in turn to test the ANN and measure errors. The mean of the results then provides a summary of overall performance. During ANN training, for each test storm, SIPSON data from a second storm are used to validate and terminate training (early stopping). The remaining 14 storms are used as target signals to train the ANN. Both target and ANN output are then post-processed to classify flood severity for each manhole at each time-step. ANN setup parameters (number of input time-steps (Nin), number of hidden units (Nhu), weight decay coefficient (α)) are varied in combination to establish an optimum setup. The results presented below are for the optimum setup (Nin = 10, Nhu = 10 and α = 10.0). Both the analogue flood level and classified flood severity data are analysed for error. Timing both for training and running the trained ANN are compared to both SIPSON simulation time and to real-time (assuming the sampling period of 3-minutes used throughout).

RESULTS AND DISCUSSIONS

RAPIDS1 – timing analysis and benchmarking

Figure 3 presents mean timings in seconds for ANN training and test for all storms. This is against a mean simulation run time of 195 seconds for SIPSON. Results are shown for a mean of samples taken at $T_{TSAdvance}$ = {0,10,20} × 3-minute time-steps. Overall, mean results for the trained ANN

Table 1 Flood severity classification scheme.

Flood class	Description	Flood depth
3	Severe	Above 5.00
2	Moderate	Between 1.00 and 5.00
1	Slightly	Between 0.00 and 1.00
0	None	Less than 0.00

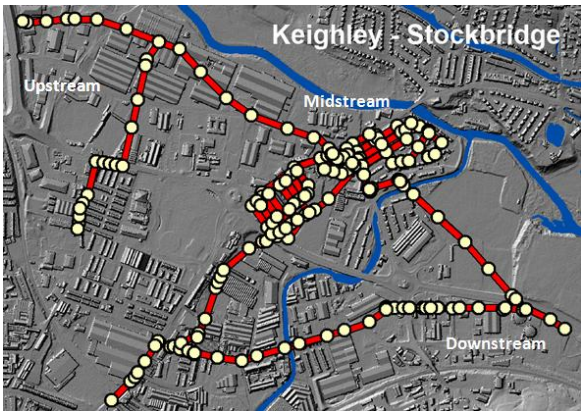

Fig. 2 GIS Map of UDN Sub-section from Keighley, West Yorkshire, UK.

were as follows. Training was typically achieved in 0.58 × mean duration of a SIPSON simulation run (i.e. 1.7 × faster). This provides the possibility of regular re-calibration of the live system, during periods of system quiescence (e.g. during periods of observed baseflows). Run times for the trained ANN for the 123-manhole UDN over a period of 6-h, with 3-minute sampling rate was better than 0.12 seconds on an Intel quad core i5-960 2.7GHz processor, running 64-bit MS Windows 7 and MATLAB 2010b.

TYPICAL FLOOD DEPTH TRACE AND FLOOD CLASSIFICATION TRACE RESULTS

Figure 4 illustrates typical ANN performance for individual manholes (ANN outputs) *vs* time-steps. Each plot has four traces: solid black: target flood level (m); solid green: ANN output flood level; dotted red: target flood severity class (0-3); dashed blue: ANN output flood severity class (0-3). The plot on the left illustrates manhole 1898's training results over all 14 storms. On the right are the corresponding test run results for a 30-minute prediction advance for manholes 1898 and 1931 for a 50-year return-period, 2-hour, design storm. Trials were conducted to analyse performance for this setup, for all 16-storms and all values of prediction $T_{TsAdvance}$.

Figure 5(a) illustrates variation of flood level percentage errors, with an overall mean of 16.0%. Figure 5(b) similarly shows variations for flood severity percentage classification errors, with an overall mean of 2.65%. Results for the 10-year RP, 3-hour storm are significantly worse than the mean for all storms. Analysis shows this is due to the UDN being at the threshold between recharge and surcharge under the catchment conditions created by this storm. Flood severity class errors for storms of 1-year RP are low because they do not lead to surcharge for the UDN studied.

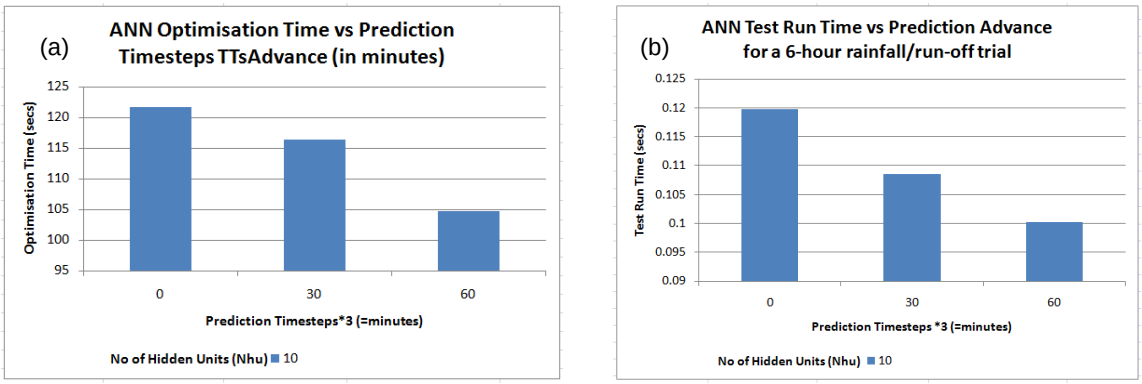

Fig. 3 (a) Optimisation time *vs* prediction advance, (b) test run time *vs* prediction advance.

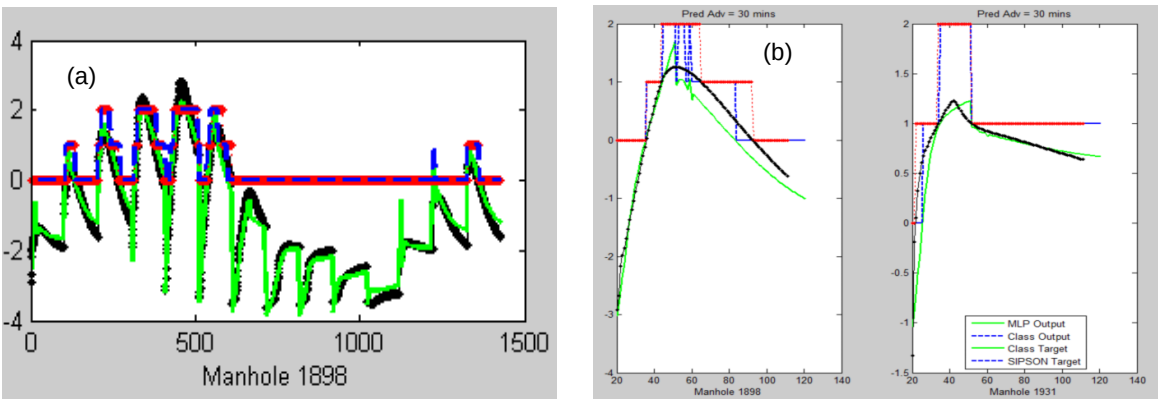

Fig. 4 (a) Typical ANN training traces; (b) typical ANN test run traces.

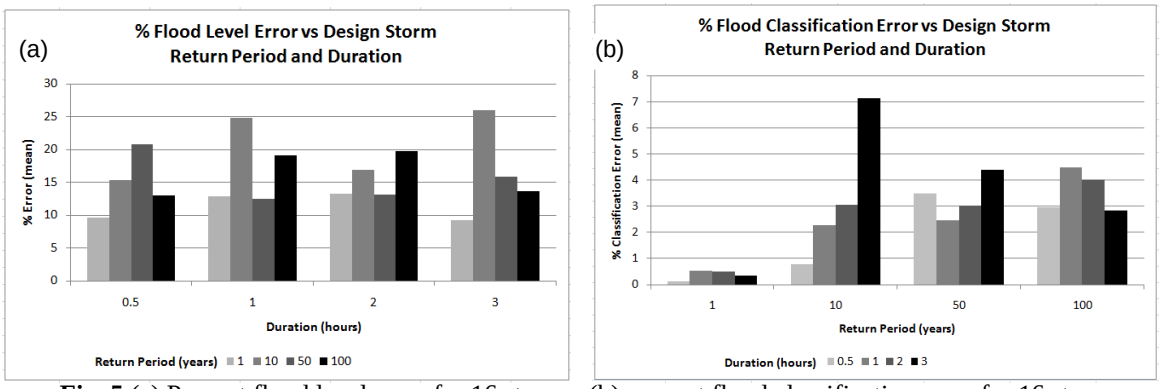

Fig. 5 (a) Percent flood level error for 16 storms, (b) percent flood classification error for 16 storms

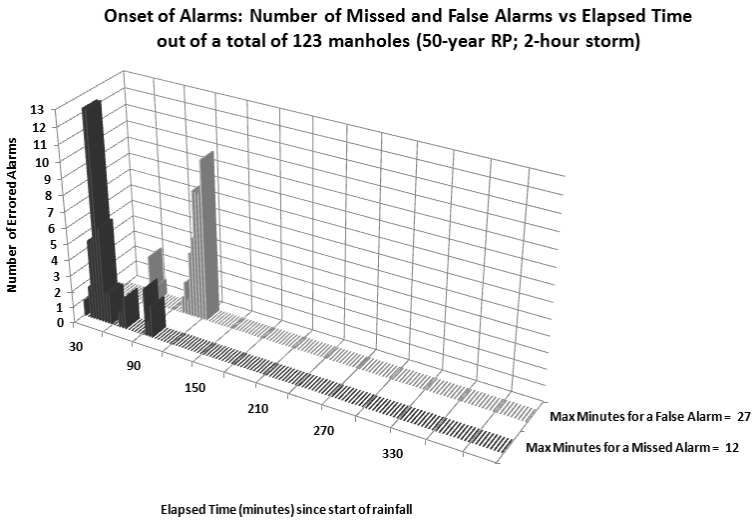

Fig. 6 Missed and false alarms *vs* time for single storm.

Figure 6 illustrates the onset of alarms across all 123 manholes (y-axis) *vs* time in min (x-axis). The two ranks show the number of missed or false alarms for a 50-year RP, 2-hour typical storm.

In this analysis, the alarm classes 1 to 3 are merged together. The maximum time during which a false alarm occurs is 27 min and for a missed alarm is 12 min. The zero-level section to the right of each rank shows that no missed or false alarm is sustained beyond the time of peak flood in this case. Calibration of the system to eliminate either false or missed alarms or achieve a trade-off between the two (as in the case illustrated) would be possible by adjusting threshold offsets for the classification wrapper function. Further analysis of the more severe (2–3) alarm states would also be worthwhile. Alternatively, a Bayesian Belief Network could be used here, not only to predict the flooding class, but also the probability of prediction. As the time goes on and the analysis is repeated, the probability would be expected to increase (or decrease). This would be invaluable to practitioners to see and assess the evolution of the storm and flooding.

RAPIDS2

The radar rainfall images used for the Keighley catchment rainfall nowcasting study contain 361 × 361 pixels, so as to allow up to 3-h storm travel time in any direction at a maximum of 60 km/h. In pattern-recognition terms, this corresponds with 130 k dimensions, since the rainfall intensity for each pixel is effectively an independent variable. Figure 7 illustrates two of the features extracted from the images: tracking of centroids (white traces) and centres-of-mass (grey traces) for each of two echoes during a storm that occurred between 28 and 30 November 2009. The longer tracks represent an elapsed time of 8.5 h. Keighley is located at the centre of the image (white square).

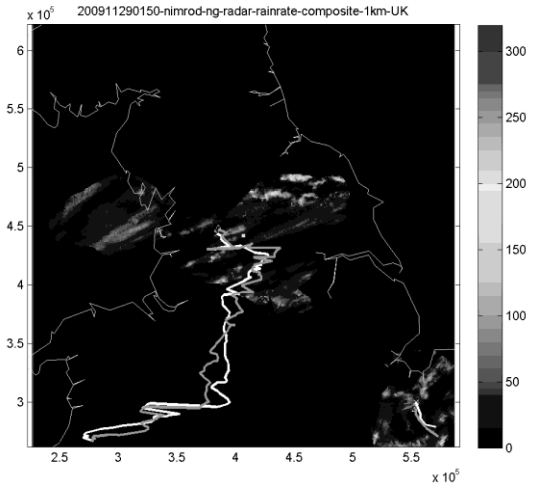

Fig.7 Tracks of centroid and centre of mass for echoes.

CONCLUSIONS

Results for RAPIDS1 show that ANNs can provide a very significant speed improvement over conventional hydraulic simulators without excessive degradation in performance. This is particularly so for flood severity classification. The method presents opportunities for automated generation of flood alarms / warnings right down to the individual manhole, including potentially for UDNs of considerable size, without being computationally expensive. However, flood prediction based on rainfall alone cannot provide operationally useful lead-times. Instead, prediction is limited in the worst case by the Time of Entry of the UDN (typically <30 min).

Possibilities for extending prediction time to operationally useful values of 2+ hours are being explored through a process of radar rainfall echo feature extraction and feature time-series prediction using ANNs. More work is needed to determine the value of this approach.

Assuming that RAPIDS2 achieves satisfactory results, the possibility of cascading the two systems to provide flood-level prediction at manholes based on live radar rainfall images will be tested.

Acknowledgment The research reported in this paper was conducted as part of the Flood Risk Management Research Consortium, with support from the Engineering and Physical Sciences Research Council, the Department of Environment, Food and Rural Affairs/Environment Agency Joint Research Programme, UK Water Industry Research, Office of Public Works Dublin, and Northern Ireland Rivers Agency. Data were provided by the British Atmospheric Data Centre, Environment Agency, Met Office, Ordnance Survey and Yorkshire Water. Our thanks go to all the above organisations for their support.

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