Predicting combined sewer overflows chamber depth using artificial neural networks with rainfall radar data

S. R. Mounce, W. Shepherd, G. Sailor, J. Shucksmith and A. J. Saul

ABSTRACT

Combined sewer overflows (CSOs) represent a common feature in combined urban drainage systems and are used to discharge excess water to the environment during heavy storms. To better understand the performance of CSOs, the UK water industry has installed a large number of monitoring systems that provide data for these assets. This paper presents research into the prediction of the hydraulic performance of CSOs using artificial neural networks (ANN) as an alternative to hydraulic models. Previous work has explored using an ANN model for the prediction of chamber depth using time series for depth and rain gauge data. Rainfall intensity data that can be provided by rainfall radar devices can be used to improve on this approach. Results are presented using real data from a CSO for a catchment in the North of England, UK. An ANN model trained with the pseudo-inverse rule was shown to be capable of predicting CSO depth with less than 5% error for predictions more than 1 hour ahead for unseen data. Such predictive approaches are important to the future management of combined sewer systems.

Key words | artificial neural networks, combined sewer overflows, cross correlation, depth monitoring, prediction, rainfall radar

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INTRODUCTION

Urban sewerage infrastructure represents highly complex distributed systems; understanding, managing and predicting the performance of these systems is extremely challenging despite being of paramount importance for society. Combined sewer overflow (CSO) structures are common assets within the UK's combined urban drainage systems. Their main purpose is to protect downstream sewers and waste water treatment plants (WWTP) from hydraulic overloads and flooding during extreme rainfall events. Spills can have a significant impact on the quality of receiving waters and cause regulatory failures. Hence, managing CSO spill pollution has become a significant concern for water companies and the efficient management of CSO assets, with catchment-wide integration, is likely to be a key enhancement to the operation of systems in the future. Improved spill prediction approaches would considerably enhance this process.

Within the UK, hydraulic monitoring of sewer systems is generally limited to short term flow surveys of around 12 weeks duration. Here, rainfall data are measured by rain gauges for a number of rainfall events and measurements of the sewer flow depth and flow rate are used to calibrate sewer hydraulic models. Measurements in dry weather flow are also made. Decreasing communication costs are allowing longer term monitoring (described by Shepherd et al. 2010) with the possibility of more in-depth analysis of large data sets and online data analysis systems. The application of rainfall radar data is one such area that has received attention in recent years and allows the fine-grained detection of spatial and temporal rainfall patterns, thus potentially improving hydraulic modelling capabilities. Currently, 85% of the UK has a resolution of 2 km or better (Met Office 2009) and most large urban catchments fall within this area. Radar data for the whole of the UK is processed by the Met Office in order to convert the reflectivity measurement into rainfall intensity and to correct potential errors such as attenuation by intervening rainfall and ground clutter. Rainfall radar data are generally supplied at a time resolution of 5 min at near real time. Previous studies have suggested methodologies for the application of radar data to urban drainage systems (Einfalt et al. 2004) and investigated the use of rainfall radar data in sewer hydraulic models (Kramer et al. 2005).

Schellart *et al.* (2012) showed that radar data provide useful measurements of rainfall, which can be applied to sewer hydraulic models with similar confidence to rain gauge data. In their research, rainfall radar data at spatial resolutions of 1 km were obtained from the Met Office, produced by a network of C-band radars that cover the UK. The work compared predicted flows from InfoWorks CS with both rainfall inputs from rain gauge and radar methods, together with actual measured flow in the sewer. The analysis was carried out using a verified InfoWorks CS sewer hydraulic model. Similar studies using hydraulic models have explored applying cluster analysis to investigate correlations between rainfall patterns and CSO behaviours (Yu *et al.* 2013).

This paper presents an approach to using an artificial neural network (ANN) for CSO performance prediction. Records of rainfall (rainfall radar) and the depth of flow in the CSO chamber are used as training data to establish the relationship between parameters. This relationship is used to predict chamber depth corresponding to subsequent verification rainfall data, without the use of a hydraulic model. Results are presented from field measurements recorded as part of a catchment case study and appropriate metrics employed to evaluate the technique. The methodology was shown to be successful and it is envisaged that a real-time version of the system could be specifically applicable to manage CSOs which are at a high risk of causing pollution and flooding failures.

BACKGROUND

Water utilities routinely gather large amounts of asset performance data. This provides abundant challenges and opportunities for the application of machine learning for monitoring, modelling and forecasting; examples include techniques for time series analysis of urban drainage data (Branisavljević *et al.* 2010), using fuzzy logic for sewer pumping station control (Ostojin *et al.* 2011) and for monitoring industrial wastewater treatment using adaptive multivariable approaches based on self-organizing maps (Liukkonen *et al.* 2013). Recent work has explored utilising rainfall radar data, hydraulic models and machine learning approaches for predicting urban flooding in real time (e.g. Duncan *et al.* 2013).

Such strategies will provide the opportunity to improve the performance of existing systems, to reduce costs, meet consents and reduce flooding and pollution incidents. Data-driven modelling has the advantage of not requiring a detailed understanding of the physical, chemical and/or biological processes that affect a system before model inputs can be mapped to outputs. ANNs have become an increasingly popular data-driven approach for water industry applications and are a modelling approach based on how biological neural systems are believed to work. Examples include use for rainfall-runoff modelling (Solomatine & Dulal 2003) and river-flow forecasting (Dawson & Wilby 1999). Evora & Coulibaly (2009) presented a review of recent advances in ANN modelling of remote sensing applications in hydrology. Li *et al.* (2010) reviewed the applicability of ANNs to urban hydraulics and hydrology whilst Kurth *et al.* (2008) demonstrated that a three hidden-layer multilayer perceptron ANN trained with back-propagation was capable of learning the underlying relationship between local rainfall occurrence and CSO response. Similarly, Guo & Saul (2011) used an adaptive linear ANN (ADALINE) to model linearly the relationship between the CSO chamber hydraulic condition (water level) and rainfall (from an in-catchment rain gauge). The ANN was used to predict, at times of dry weather and in response to rainfall, the hydraulic performance of a CSO in terms of flow depth. Using rainfall and depth as lagged inputs, the chamber water level for 3 time steps ahead (15 min) was successfully predicted for a number of assets.

CASE STUDY

Catchment and data sources

Some UK water utility companies currently monitor many of their CSO assets with telemetered ultrasonic water level sensors. The data from one such CSO has been used in this study. Situated in the north of England, the CSO serves as the terminal flow control to a treatment works at the bottom of a steep combined urban drainage catchment. The catchment serves a population of ~11,000 people in several small towns spread over ~20 km^2 of a substantively rural area. A schematic of the catchment is shown in Figure 1. The chamber, installed in around 2004, is a recent design of single high side weir (9 m long, 2 m wide with weir height 1 m), incorporating rotary screens along the 5.5 m weir length. Flows from events with a return period greater than 5 years are designed to overtop the screens to preserve hydraulic capacity in the network. Time series water level data within the CSO was recorded using an ultrasonic depth monitor producing an instantaneous reading every 15 min, with the depth recorded as a percentage; a figure of 100% generally calibrated to spill
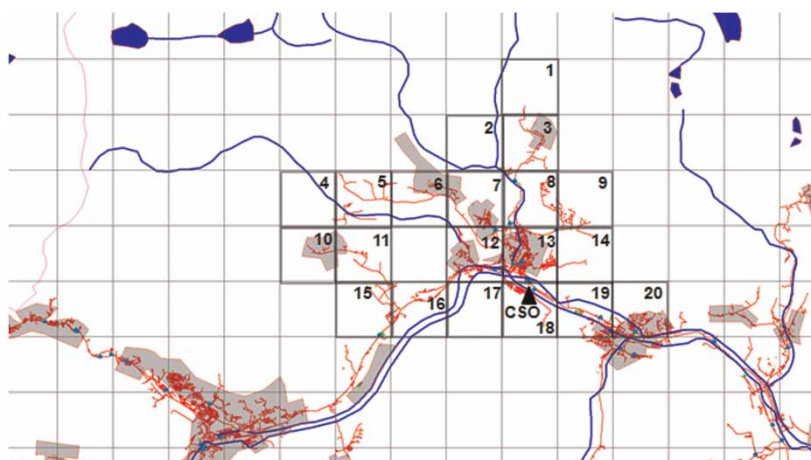
Figure 1 | Case study CSO and rainfall radar grid square coverage.

level (analysis of the data suggests the spill level at this particular site is over 160% but this calibration discrepancy is unimportant to the key findings of this paper). Rainfall intensity data (mm/hr) from 20 (numbered) rainfall radar pixels (1 km^2 resolution), which covered the sewered area, were collected continuously for a period of 6 months from 13/06/2012 to 31/12/2012. The rainfall intensity data were supplied at a time resolution of 5 min, but were aggregated to 15 min to match the CSO level data. Figure 1 also shows the river/canal overlay (dark), urban blocks (shaded grey) with the sewers as fine lines.

Runoff from a storm over an urban catchment initially flows overland, before entering the sewer system to be carried downstream to the CSO. This runoff time and sewer flow time causes a time difference between recorded rainfall and the response at the CSO chamber. It may be exacerbated by the spatial and temporal distribution of the rainfall over the catchment, including speed and direction of travel. Note that there is a slope ratio of ∼ 1 in 20 present.

METHODS

Data analysis and determination of input data

Initial data analysis was conducted in order to determine appropriate inputs. First, all data were assembled and pre-processed for any missing data points. The coefficient of correlation was then calculated between rainfall intensity (mm/h) from each of the 20 grid squares and the CSO depth. These positive values varied between 0.175 and 0.241 (mean 0.218) with the top 6 squares being 1, 2, 3, 5, 6 and 7. However, Pearson's *r* does not provide any

information concerning lagged versions of time series data. The underlying relationship between local rainfall and water level in a CSO chamber will occur with a certain lag time. When a rainfall event occurs in the contributing catchment, the CSO reacts with a rising water level in its chamber, whereas under normal conditions during dry weather, the water level presents a relatively stable diurnal pattern.

Cross-correlation is a measure of the similarity of two variables (signals) as a function of a time lag between them (Bracewell 2000). It achieves this by aligning peaks (or troughs) across the two signals at different lags and hence can be used to determine the time delay between two signals. The cross correlation between the CSO depth and rainfall data (and the serial correlation to explore auto correlation for depth) were thus investigated. This method has previously been successfully used for similar studies (Fernando *et al.* 2006) to determine the size of the model input in order to capture the underlying process effectively. Equation (1) gives the cross correlation and Equation (2) the serial correlation

$$y \otimes u = \bar{y}(-t) * u(t) \tag{1}$$

$$y \otimes y = \bar{y}(-t) * y(t) \tag{2}$$

where *y* is the depth, *u* the rainfall intensity, ∗ a convolution function and $\bar{y}(t)$ is the complex conjugate of $y(t)$.

Twenty cross-correlations were applied to the data sets, using the XCORR function in MATLAB® R2012a (The MathWorks Inc., Massachusetts). The maximum of the cross-correlation function indicates the point in time where the signals are best aligned. Figure 2 shows a graph of the
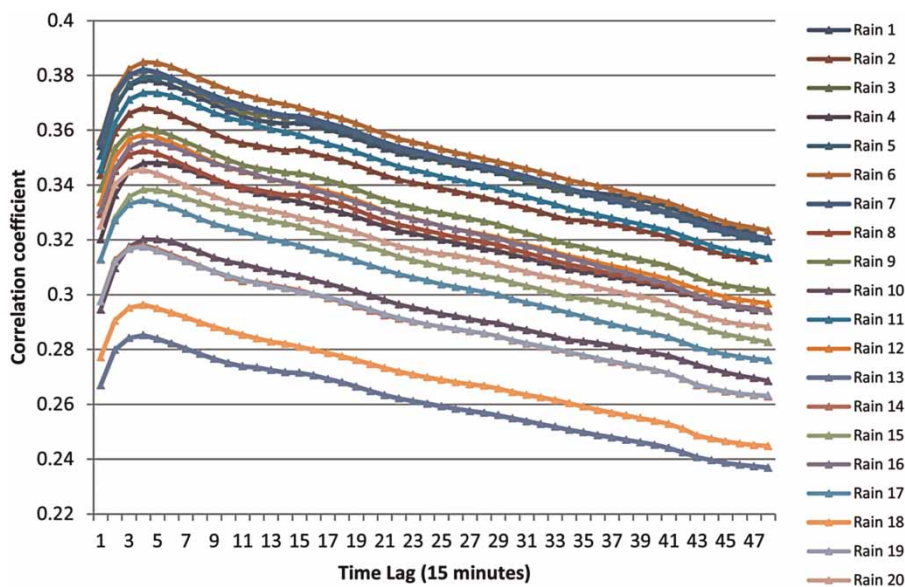
Figure 2 | Cross correlations between depth (y) and rainfall intensity (u).

correlations for each rainfall radar cell for a range of time lags. The cross-correlation maximum varied between 0.29 and 0.38 at either time lag −4 or −5 (corresponding to 1 hour to 1 hour and 15 minutes). The larger maximum correlation squares were 1, 3, 6 and 7. The longer time delay of −5 was observed in the far western grid squares (4, 5 and 10). While a full hydraulic model for this catchment was not available, this figure is close to an estimate of the time of concentration. A greater geographic separation in rainfall radar squares would be expected to show a wider range of peak cross correlation values.

For most radar squares a good choice for a temporal window with a high correlation would be a lag of between 2 and 12. Conversely, for serial-correlation in depth, the correlation values decrease gradually from unity, as would be expected, with increasing lag time.

Model implementation

One of the most straightforward ANN architectures is a single layer feed-forward network with single output. One such structure is the standard perceptron with weights, a bias and a summation function. A number of learning rules can be used to train this network. The Hebb rule is based on the correlations of each input with the output through every prototype. A generalisation of the Hebb rule is the pseudo-inverse rule defined by Equation (3)

$$\mathbf{w} = \mathbf{b}\mathbf{A}^+ \tag{3}$$

where $\mathbf{w}$ is the weight matrix, $\mathbf{b}$ the output vector, and $\mathbf{A}^+$ the Moore–Penrose pseudoinverse of the input vector (Penrose 1955). A common use of the Moore–Penrose pseudoinverse is to compute a least square errors solution to a system of linear equations that lacks a unique solution. Consequently, the matrix defined by (3) is the one that minimises the error $\|\mathbf{w}\mathbf{A} - \mathbf{b}\|$ on the output space.

An alternative learning rule is the ADALINE rule, also referred to as the delta rule or Widrow–Hoff rule (Widrow 1962) as defined in Equation (4), with t time η_t the learning rate

$$\mathbf{w}(t+1) = \mathbf{w}(t) + \eta_t(\mathbf{b} - \mathbf{w(t)A})\mathbf{A^T} \tag{4}$$

The ADALINE rule produces its best solution on the convergent point, which is $\mathbf{w} = \mathbf{b}\mathbf{A}^+$ (Mayoraz 1990). Hence, the pseudo inverse rule is utilised here for hydraulic performance prediction. Guo (2011) found that the relationship between CSO hydraulic condition (flow depth) and rainfall (from rain gauge data) was capable of being modelled in this way i.e. with a single layer ANN (no hidden layers). Thus, a moving time-window approach can be implemented for the case study CSO whereby lagged time-series signals (rainfall intensity and depth) are provided in parallel over the time-window as inputs to the network. The model development and data pre-processing (such as normalisation) were carried out using MATLAB®. Several ANN models (ANN-N) were consequently developed for forecasting the current to p future value of the depth rate

$y(t)$ to $y(t + p)$ thus consisting of $n + m$ input nodes (n antecedent depth data y and m antecedent rainfall data u from grid square X). For example, ANN-1 used rainfall radar data from grid 6, with rainfall input to forecast $y(t)$ being $u(t)$, $u(t–1)$, $u(t–2)$, $u(t–3)$, $u(t–4)$, $u(t–5)$, $u(t–6)$, $u(t–7)$, $u(t–8)$, $u(t–9)$, $u(t–10)$ and depth input values $y(t–1)$, $y(t–2)$, $y(t–3)$, $y(t–4)$, $y(t–5)$, $y(t–6)$, $y(t–7)$, $y(t–8)$. Hence, the rainfall intensity parameter u was always one data step ahead of the chamber water depth parameter y.

RESULTS AND DISCUSSION

Several ANN models, as described in the methodology, were constructed and the data for the case study catchment used to assess performance. Predictions for the chamber depth were attempted for p time steps ahead (15 min to 1 hour and 15 min). A representative training set was constructed containing both dry and wet weather periods (approximately 50% of the overall period). This model was then applied to a subsequent test period. A number of rainfall radar pixels were used and three are included here. Training and test performance is given in Table 1. In this paper the root mean squared error (RMSE), as defined in Equation (5), has primarily been used to evaluate the predictive accuracy of the model

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \sum_{j=1}^{m} (o_{ij} - t_{ij})^2}{n}} \qquad (5)$$

where n is the number of patterns in the validation set, m is the number of components in the output vector, o is the output of a single neuron j, t is the target for the single neuron j, and each input is denoted by vector i. A value was also calculated, which scaled the error by the predicted water depth i.e. to give a percentage error per time step.

It can be seen from Table 1 that the model prediction accuracy is reduced as the prediction range is increased. A range of input lags (identified by cross correlation) provide a good performance, and it is concluded that model accuracy is sufficient to provide a prediction of CSO depth with only 2% error on a 1 time step ahead prediction (15 min) for unseen data, and with less than 5% error in all models for predictions 5 time steps ahead (75 min). An example of the application of the ANN-1 model, with a prediction of performance 15 min (1 time step) in the future is shown in Figure 3. There is excellent agreement between the predicted and observed depth for unseen data. Figure 4 shows the prediction for a period in which spilling occurred following rainfall. A 1 hour ahead (4 time steps) prediction is plotted in order to assess the potential effect of rainfall at the CSO (so the prediction has been shown 4 time steps advanced). It can be observed that for periods of rainfall, an increase in chamber depth is anticipated ahead of time, thus illustrating the potential of the model.

When considering Figure 4, it is also of interest to compare overflow volumes calculated from measured and simulated depths using the standard thin plate weir formula (based on a weir crest at 164%). For the totality of the test data (nearly 3 months' data), the measured cumulative overflow volume was 3,862 m^3. The predicted cumulative

Table 1 | ANN models and metric results

|	Radar Grid square	Architecture		p	Train RMSE	Train %	Test RMSE	Test %
		u delay (m)	y delay (n)					
ANN-1	6	11	8	1	5.19	2.74	3.97	1.99
ANN-2	6	8	6	1	5.20	2.73	3.97	1.98
ANN-3	6	15	10	1	5.18	2.75	3.97	2.00
ANN-4	6	11	8	2	7.91	4.66	4.54	2.72
ANN-5	6	11	8	3	10.03	6.34	5.42	3.84
ANN-6	6	11	8	4	11.97	8.22	6.11	3.97
ANN-7	6	11	8	5	13.73	10.23	6.58	4.28
ANN-8	5	11	8	1	5.23	2.74	3.94	1.97
ANN-9	5	11	8	5	13.84	10.39	6.35	4.32
ANN-10	18	11	8	1	5.37	2.68	3.98	2.27
ANN-11	18	11	8	5	14.55	11.27	5.71	4.07
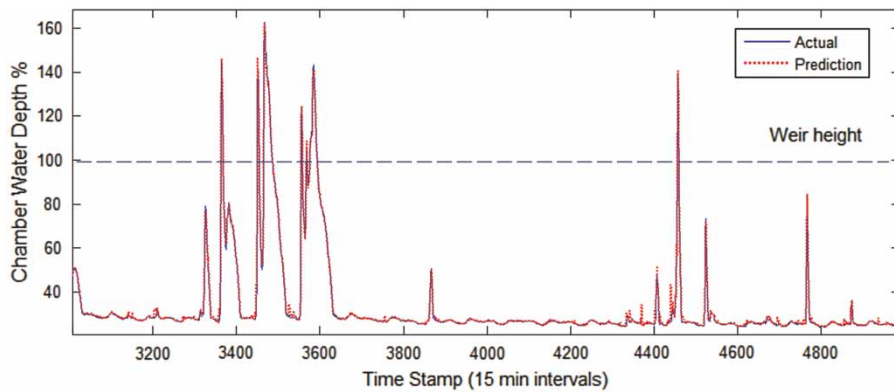
Figure 3 │ Model prediction and measured flow depth.
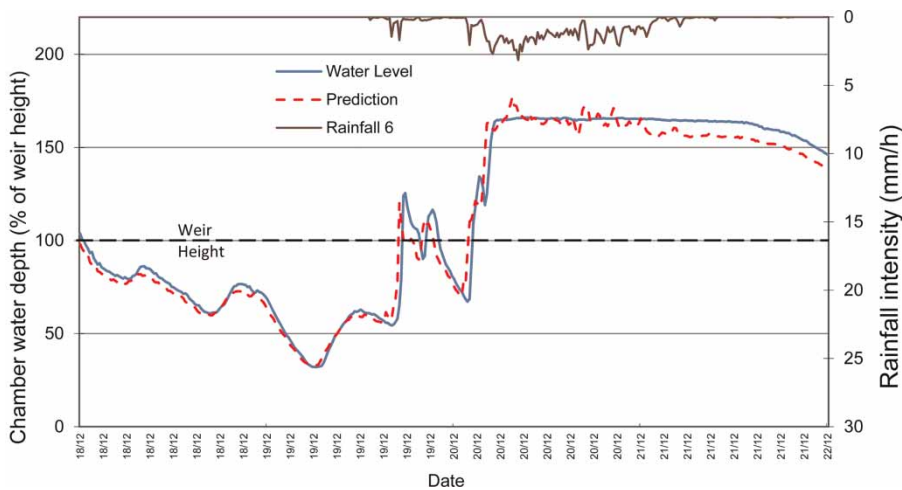
Figure 4 │ Model prediction (1 hour ahead) for selected period.

overflow volume was 9,288 m³. Hence, there was a large over-prediction of overflow volume due to relatively small errors in the depth prediction. We can conclude that the architecture is not optimised for this prediction, which was not the intention of the methodology.

For reasons of brevity, full details of the model sensitivity tests, including the derivation of training-set length and other validations conducted, are not presented but the interested reader is referred to Guo (2011). However, Table 2 provides some sensitivity tests conducted as regards the training and testing sets using different input data along with a range of error metrics. Note that $m = 11$, $n = 8$ and rainfall radar square is 6 (when rainfall u is incorporated as an input). We see that including the rainfall in the input (columns 1 to 3) versus the equivalent columns where depth only is used (indicated as y only), generally only improves prediction accuracy marginally for training data,

and sometimes not at all for testing. However, using only rainfall data and no depth in the input (final column) results in very large errors and, in this case, actually higher error on the test set.

Due to an artefact of the data set division, the performance is actually better for the test set for the networks featured in Table 1 (and in most cases in Table 2) contrary to normal ANN applications. The training period covered mid-June to late September, while the test data period was for the months October to December. Evidently these two periods will possess quite different rainfall patterns. There was 6.4% more rainfall depth in the training data and it tended to be more intense. However, a more significant factor was that when the characteristics of the data sets were examined in detail, it was discovered that the training set had a particular period with CSO depth values significantly above 170%, whereas there is a clear cut-off in

Table 2 │ Sensitivity tests

Type	p = 1, y and u		p = 4, y and u		p = 12, y and u		p = 1, y only		p = 4, y only		p = 12, y only		p = 1, u only	
	Train	**Test**	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**	**Train**	**Test**
% error	2.7	2.0	8.2	4.0	21.4	7.8	2.9	1.7	10.9	3.6	23.5	7.9	58.8	75.8
R^2	0.987	0.993	0.929	0.985	0.781	0.968	0.984	0.993	0.907	0.990	0.763	0.973	0.223	−0.075
MAE	1.53	1.48	4.80	3.40	10.5	6.12	1.44	1.39	5.20	2.59	10.96	5.52	30.80	40.15
RMSE	5.19	3.97	11.97	6.11	21.03	8.8	5.64	4.14	13.72	5.03	21.85	8.04	39.60	50.92
MASE	1.04	1.02	3.26	2.34	7.14	4.22	0.98	0.96	3.54	1.78	7.45	3.80	20.95	27.65

values for the test data around 170%. This appears to skew the results at the highest depths, which affects the training set with higher errors compared to the test set. It is suspected that either the monitor or the CSO had a minor issue during this first 3 months, i.e. during the training period. The training and test sets were switched around and, using the parameters of ANN-1, we get 1.9% error in training and 2.6% error in testing; i.e. a more normal performance on test data. So the performance of the CSO during the first 3 months is less predictable with the architecture than in the later period.

Clearly there are many potential applications for the model in respect of identifying unexpected performance or in a gradual change (e.g. silt build-up). Development of the model is ongoing in order to provide this type of interpretation capability. In particular, online processing of data could allow the prediction of CSO performance failures (such as spill events) much earlier and potentially in real time. A full decision support system will also necessitate further classification of model outputs, perhaps using fuzzy/Bayesian inference systems or a binomial event discriminator. While the work described has only used measured rainfall, there is the potential to use predicted rainfall (using nowcasting) as an input to the model. However, this type of forecasting would naturally lead to a greater degree of uncertainty and potentially larger errors. There is also significant potential for applying these techniques to other sewerage asset types such as Detention Tanks and Sewer Pumping Stations with a view to enabling wider network performance visibility.

underlying relationship between contributing local rainfall (using radar data) and the water level within a CSO structure downstream. A case study example has shown how rainfall radar data correlate with certain time delays to CSO chamber depth. An ANN model trained with the pseudo-inverse rule was shown to be capable of providing prediction of CSO depth with less than 5% error for predictions 5 time steps ahead (75 min) for unseen data. This shows improvement on previous studies using tipping bucket rain gauge measurements. In theory, the longer the range of the rainfall prediction available, the further the water depth can be predicted into the future. However, in practice, rainfall prediction errors will limit the forecast time of the technique. This tool offers the potential benefit of early detection of unexpected performance behaviour and the identification of various failure modes in both dry and wet weather conditions, thus enabling pollution incidents to be managed more proactively. The approach is a very useful alternative to developing a full physical-based model of a catchment, removing manual modelling overheads and the data requirements of calibration.

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CONCLUSIONS

Rainfall radar data offer a data solution for near real-time operational strategies. This work has demonstrated the potential of a data-driven approach in capturing the

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