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The Use of Telemetry Data for the Identification of Issues at Combined Sewer Overflows

James Bailey[a, b,*], Emma Harris[a], Edward Keedwell[b], Slobodan Djordjevic[b], Zoran Kapelan[b]

[a] *Dŵr Cymru Welsh Water (DCWW), Pentwyn Road, Nelson, Treharris, Mid Glamorgan CF46 6LY, UK*
[b] *University of Exeter, College of Engineering, Mathematics and Physical Sciences, Exeter, UK*

Abstract

Issues at Combined Sewer Overflows (CSOs) affect water and sewerage companies' serviceability performance, can result in environmental impacts through discharges to watercourses, which can incur large costs due to financial penalties for pollution incidents. There is increasing telemetry coverage at CSOs, increasing the availability of data regarding asset performance. This paper presents the application of Artificial Neural Networks (ANNs) to the telemetry data of Dŵr Cymru Welsh Water, alongside RADAR rainfall data, to predict level and provide the identification of issues at CSOs.

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Keywords: Wastewater, CSO, ANN, Blockage, Detection

1. Introduction

Combined Sewer Overflows (CSOs) are installed within the wastewater network to alleviate any flows beyond the capacity of the network, to prevent the potential flooding of properties. With a designed flow which is passed forward, any flows beyond this can be discharged to the receiving watercourse. However, incidents such as blockages within the chamber of the asset can result in the asset discharging during dry weather, potentially resulting in sewage being discharged to the environment, and pollution of the receiving watercourse.

Level monitoring can now be used to monitor the performance of the asset and provide an alarm to highlight when the level indicates the asset is, or is close to, discharging to the environment. This notification alerts the

* Corresponding author. *E-mail address:* j.bailey@exeter.ac.uk

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operators of the discharge, at which point a decision must be made on a course of action. Rainfall data can be used to help evaluate whether the discharge is due to rainfall or the result of an issue such as a blockage causing the level to rise beyond what would be expected given the preceding rainfall. An understanding of how the asset is performing is required to enable the appropriate response to be made, for example requesting site attendance for further investigation if necessary.

CSOs are now being subjected to increased scrutiny as part of the Event Duration Monitoring (EDM) requirements introduced by the Environment Agency (EA) in England and Natural Resources Wales (NRW) in Wales [1]. This requires Water and Sewerage companies (WaSCs) to monitor assets and report on the performance in terms of the number of discharges, which in Wales will result in all CSOs being monitored [2]. Further scrutiny is being provided by users of beaches and bathing waters increasing the demand for improved performance and increased access to data, through advanced warnings of discharge which may affect beach or water quality [2]. Under this scrutiny there is a need for increased understanding of the performance of the asset to inform the understanding of why discharges occurred, the overall performance of the asset and prioritise where investment may be required.

There is an increasing amount of level monitoring at CSOs, further driven by the EDM regulations. This increase is tied with reductions in the cost of data storage and the improved processing power of computer systems to handle these large quantities of data. The amount of rainfall data has also increased with the installation of the Met Office's network of RADAR rainfall measurements, which continuously provides rainfall readings at a resolution of up to 1km [3]. This has led to the increased availability of data which can be used to assess asset performance, as well as an increased number of assets which need to be monitored within the control rooms of WaSCs, and an increased number of potential alarms which need to be processed. During extreme weather events this can lead to a large workload being placed on these control rooms to process and respond accordingly to each alarm which is received.

The increasing amount of data is being supported by the development of data-driven modelling techniques which allow patterns within the data to be used to derive relationships, without the need for detailed hydrodynamic models of catchments to be developed [4]. However, factors such as the permeability of the ground, which will be affected by the rainfall which has occurred in the recent past, will in turn affect the speed and size of the response to rainfall events. Artificial Neural Networks (ANNs) offer a potential data-driven modelling technique which can derive relationships for the response of the level to rainfall events which occur. Mounce [4] used the rainfall and level readings within a catchment to predict the level at the asset up to 75 minutes into the future with a less than 5% error. The aim of this was to provide WaSCs an advanced warning of the asset's likelihood of discharging, allowing a response to be made, preventing the asset from discharging. The prediction of the level at assets, based on the preceding rainfall which has occurred, could have implications for WaSCs in terms of understanding and responding accordingly to each of the alarms which are received, providing automated notification of anomalous behaviour of assets and understanding the overall performance of assets. These automated notifications could be the gradual build-up of a blockage within the chamber causing the level to rise beyond the expected, events which could potentially be detected early, before the asset has alarmed or discharge occurred, and allow the WaSCs to deploy operators to the site and prevent the site from discharging and any potential environmental impacts.

This paper presents the use of ANNs to predict the level at an asset, based on the preceding rainfall, with the aim of detecting blockages which have occurred using the anomalies between the predicted and actual level readings.

2. Methodology

The decision was made to produce individual models for each site, given the likely different responses to the rainfall for each asset. The first stage in the process was therefore the selection of a site for demonstration, followed by the level and blockage prediction.

2.1. Data Sources

The data sources used were the level and rainfall telemetry readings, an incident log maintained by Dŵr Cymru Welsh Water's (DCWW's) control room and DCWW's SAP system, containing the records of jobs completed by operators. The level readings were taken from the corporate system of DCWW, which contains the ultrasonic level meter readings from the chambers of the CSO assets. The level readings are taken every 15 minutes, with the levels at the demonstrate site representing a percentage reading, 100% being the spill point of the asset. A data quality assessment was made to evaluate the amount of missing data and outlying values.

The rainfall data used was originally from the Met Office's RADAR rainfall, which is sourced and held by DCWW, from where it was sourced for this project. The rainfall data is held at 5 minute intervals for 5 km grids, with the data aggregated to 15 minute readings to match the frequency of level readings. The data was checked for data quality, investigating the amount of missing data, and any outlying values. The decision was made, given the amount of telemetry data which was available, and low levels of missing data, not to infill any of the missing rainfall data, but to exclude these periods from the analysis.

DCWW's control room maintains a log of level alarms which occurred and for which an operational crew was requested to attend. The log also records the results of the attendance, for example if a blockage at the asset was found. This dataset was used to assess the sites which had suffered the greatest number of blockages and were candidates for modelling, and to define the blockage events which had occurred, which the model aimed to detect. A visual assessment of the telemetry readings before and during the blockage events was completed to understand the period over which the blockages formed and abnormal behaviour of the asset was observed. A period of time was defined during which this abnormal behaviour was observed, and this data was removed from the dataset used to train and test the level prediction model. The details on the blockage were further informed using DCWW's SAP system which contains records of the jobs created for a crew to attend sites, and any associated notes made. This information was used to give further detail to the information on the situation in which the blockage occurred.

2.2. Data Audit

To select the demonstrate site for modelling, the records of the number of blockages suffered by each site was used to produce a prioritised list of potential sites. A data quality assessment was then made to exclude any sites which showed poor data quality. This assessment included the evaluation of the number of missing and negative values, periods of flatlining and outlying values.

Once a demonstration site had been selected, further information was sought on the details of the asset, and the size and location of the upstream network. The upstream network was investigated using a network trace which moved from the asset through each of the connecting chambers and sewers, until an end point in the network was found, calculating the length of network between each chamber and the site. Each sewer was spatially joined to a RADAR rainfall area using Geographical Information System (GIS) software. The rainfall area labels and length of network was used to produce a distribution of network length for each rainfall area, giving information to allow the likely time lags between the rainfall occurring and the effect on the level readings for the site to be. The upstream network was also checked for the presence of any pumped flows or nearby assets which would impact the level response of the asset to rainfall.

A correlation analysis was conducted to evaluate the relative importance of each rainfall area for predicting level, and the required range of rainfall data to be used as an input to the ANN model of level. The heaviest periods of rainfall were selected and the Pearson linear correlation coefficient between the level reading and the rainfall at different time lags evaluated. To define the rainfall events, the start of an event was defined as the occurrence of any amount of rainfall. The end point was defined by a period of time during which no rainfall occurred. This period of time of time was defined by a visual assessment of the telemetry trends, and the typical time taken for the level reading to return to normal, following the end of a rainfall event. The rainfall events were defined and the average rainfall intensity found for each event, with any events corresponding to periods when blockages occurred excluded, given the likely abnormal behaviour which would be observed. The top four heaviest rainfall events by average intensity were selected and used for the correlation analysis.

2.3. Modelling – Level Prediction

ANN models were built for the prediction of level using a multilayer perceptron within the IBM SPSS Modeler software [5]. The number of hidden layers used was set to one, with the number of hidden nodes optimised using a built-in algorithm within the software. Models were built using the level and rainfall readings, or the rainfall readings alone as inputs, with the time of day used as an input to aid in the prediction of any diurnal patterns observed by the site. The length of historical data used was informed by the correlation analysis completed, with the point at which the correlation coefficient receded towards zero used to define the time period for input. Any missing values within the data were deleted listwise. The models were evaluated using the measurement of the error in the level readings and the correlation between the actual and predicted levels.

Training and testing partitions were used within the model building, with any periods of blockage excluded from the level prediction modelling. The training and testing periods were defined using a time cut-off in the data, with one part used for training and the other for testing. The periods were defined with the aim of selecting similar patterns in the rainfall to ensure the model was trained and tested using representative rainfall events.

2.4. Modelling – Blockage Detection

Using the output from the level prediction model and the actual readings for the level, a classification procedure was used to detect blockages which had occurred, defined from the control room log of incidents. A visual assessment of the telemetry trends and the abnormal behaviour of the level response during the build-up of a blockage were investigated to select a period of time for defining as the blockage event. To classify readings, a number of error measures were defined, with different thresholds within these investigated to define an alarm for a potential blockage. The error measures defined were the model error, the difference between the actual and predicted levels with negative readings defined as under prediction, the absolute error, and the error relative to the predicted level. For each of these measures, different temporal thresholds were investigated, with the minimum, average and maximum calculated for the aggregation of the values. The definition of detection was defined as an alarm at any point during the time period of interest. The negative periods, during which no blockage was occurring, were created by the definition of a time period, with the time outside of the blockages separated into windows of this length. For this, the time window used was one day in length. Partitions for the evaluation of blockage detection were defined using the same cut-off used for the level prediction partitions, with the periods of blockage included within the data used for evaluation. The classification performance was evaluated using an ROC curve and the calculation of the area underneath.

3. Case Study

The demonstration site used was a CSO with an approximate depth of 500mm and containing a hydrobrake, fed by a 375mm diameter sewer, with a 375mm outfall and 300mm downstream pipe. The upstream network is up to 430m in length, overlapping two 5km rainfall areas. The catchment feeding the CSO is gravity fed, with no upstream assets which may affect the level response to rainfall. The level readings for the site are made at 15 minute intervals, with the level data sourced for a two year period between 01/06/2013 and 01/06/2015. It was subsequently found that the asset had been altered to remove the hydrobrake, and so the upper date range used was limited to 01/09/2014, the point at which the hydrobrake was removed.

4. Results and Discussion

4.1. Data Audit

The correlation analysis (Figure 1) showed similar results for the two rainfall areas which the network overlaps, with the linear correlation coefficient receding to zero within a four hour time lag. The analysis also showed a high level of correlation between the two rainfall areas at a zero time lag. Given the time taken for the correlation to recede, four hours of preceding rainfall and level data were used as inputs to the ANN model.

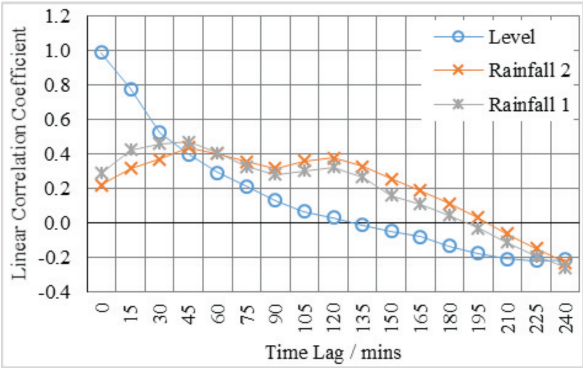


Fig. 1. Results of the correlation analysis for the site. The chart shows the correlation between the level at time 0 and the level and rainfall readings at different time lags.

4.2. Modelling - Level Prediction

The results in Table 1 show the performance of the two models built using the level and rainfall, or the rainfall readings alone as inputs to the model. Based on the training and testing partitions, model 1 would appear to outperform model 2, with lower values for the mean, mean absolute error and root mean square error (RMSE) and higher values for the correlation. Given the likely similarity between consecutive level readings, and the high correlation at a time lag of 15 minutes for the autocorrelation of level it would be expected that the use of this input would improve level prediction. However, investigating the blockage partition shown in Table 1 and the telemetry plot for a blockage event (Figure 3) which was selected as being the simplest to predict, given the information held on the response to the blockage and the simple nature of the sudden change in level given no preceding rainfall. Table 1 shows that the blockage partition shows a high linear correlation coefficient, with similar values for the mean absolute error and RMSE as the testing partition. From Figure 3a, it can be seen that when the site is discharging the level readings often remain very consistent, which when combined with the high influence of the previous level reading in the ANN model results in an initially large error in the prediction, before the predicted and actual level become closely aligned. The aim of the approach for this type of blockage would be that the predicted level remains constant while the actual level spikes, causing a large under prediction which can be used to detect the occurrence of the blockage. For Model 2, the error results shows significantly poorer performance for the periods of blockage, with Figure 3b showing the desired outcome of a consistent level prediction causing a large error in the model to occur. Given these reasons, Model 2 was selected for use in the blockage detection part of the work.

Table 1. Table of results for the models predicting the level at the CSO. The table gives the results in terms of the error, including Root Mean Square Error (RMSE) and the linear correlation coefficient.

Model 1	Training	Testing	Blockages
Mean Error	0.2	-0.3	2.7
Mean Abs. Error	5.4	6.1	6.1
RMSE	11.5	13.0	12.0
Linear Correlation	0.89	0.83	0.92
Occurrences	14746	19606	9519

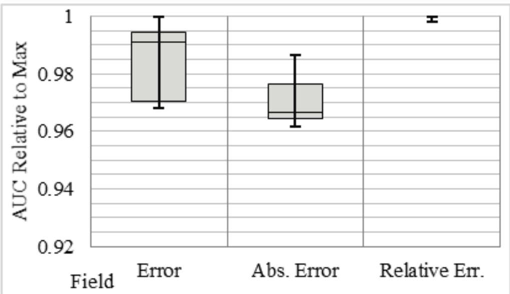
Model 2	Training	Testing	Blockage
Mean Error	0.2	-1.0	11.3
Mean Abs. Error	9.3	9.3	14.8
RMSE	16.6	16.8	29.0
Linear Correlation	0.76	0.68	0.34
Occurrences	14746	19606	9519

4.3. Modelling – classification of issues

Table 2 shows the results from the classification of blockage incidents using the different variables defined based on the different fields, aggregate functions and temporal thresholds. Table 2 shows a generally good classification performance, with the AUCs ranging between 0.92 and 1, although, given the large number of negative events, even a small increase in specificity from 0 can result in a large false alarm rate. The best performance is given by the variable using the minimum absolute relative error over a temporal range of 12 readings (3 hours), showing an AUC of 0.996.

Figure 2 shows the performance for each of the variables investigated. For each model the AUC relative to the maximum AUC for that model was found, with the range of these relative AUCs used to produce a boxplot to show the effect of each variable. Figure 2a shows that the relative error appears to be the best performing field across the variables derived. The box plot shows a very narrow distribution for this field, consistently outperforming the absolute error, and the error in the majority of cases. The relative error takes into account the predicted level in the derivation of this variable. Blockages with no or very low rainfall are characterised by predicted levels which remain close to normal, and actual level readings which show large increases, as shown in Figure 3b. The relative error will show larger negative values for these blockages, which should be the simplest to predict, than for blockages where there has been some rainfall, likely causing increases in the predicted level, for the same value of error, thereby improving the classification of the dry weather blockages.

Figure 2b shows the effect of the temporal threshold used, with the number of readings of 12 appearing to perform the best. The box plot shows 12 readings having a similar range as 1 to 8, but with a narrower interquartile range and higher median which would suggest it shows the best performance. Using a single value for the

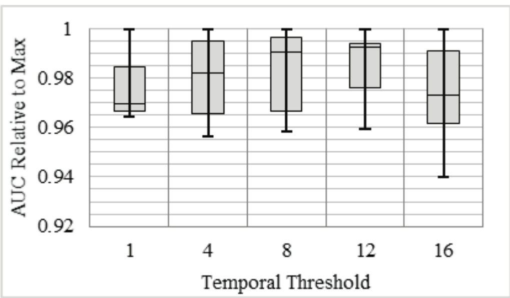


(a)

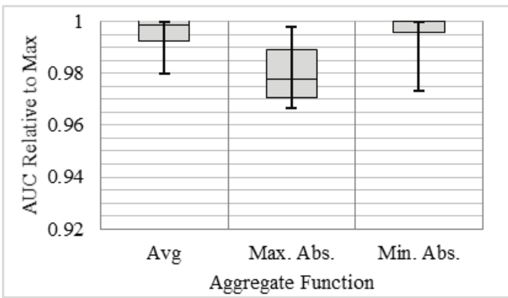
	Error	Absolute Error	Relative Err.
Max. AUC	0.988	0.985	0.996
Avg. AUC	0.967	0.957	0.985
Min. AUC	0.940	0.921	0.960

Table 2. shows the results for the classification of the blockage events, giving the maximum, average and minimum area underneath the receiver operator characteristic curve (AUC)

Fig. 2. the charts show boxplots for the distribution of the AUC relative to the best performing model of each type, for each of the model runs. (a) shows the effect of the field used, (b) the effect of the temporal threshold and (c) the effect of the aggregate function.



(b)



(c)

classification could result in a single reading with a large error causing an alarm. The use of a greater number of readings within the variable will result in the requirement for a longer period of divergence between predicted and actual, negating the effect of any single erroneous readings. The performance seems to reduce again when the number of readings is increased to 16, which is equal to the range of the input data used. This may be due to the small influence of readings between 3 and 4 previously for predicting the current level. The improved performance of 12 hours may be due to a correspondence with the typical length of blockages, providing the optimum range over which to check that divergent readings have been received.

Figure 2c can be used to evaluate the effect of the different aggregate functions used. The figure shows that the average and minimum absolute values show similar performance in terms of their range and interquartile range, with the minimum absolute value showing better performance in terms the median value, therefore appearing to provide the best results. The minimum absolute value represents the case where all of the values are required to be beyond a certain threshold, where there is a consistent period of values greater than the defined threshold. The maximum absolute value gives weight to the largest value within the range, a value which may be erroneous, resulting in poorer performance. The average takes into account all of the values within the period used, and could be skewed by the presence of largely erroneous values, although it is less likely to be skewed than the maximum absolute value. This function therefore shows performance which is similar to, although slightly worse than, the best performing aggregate function for each field.

Overall the variables defined would seem to give good classification performance, enabling the automated notification of issues at the site to be provided. Further work could be conducted to use more sophisticated classification techniques which would improve the performance, or may be required for other sites which show less clear definitions of blockages for these alarm definition variables.

5. Conclusions

This paper demonstrates the use of artificial neural networks to produce a model predicting the level at a combined sewer overflow (CSO), the output from which is used to detect the occurrence of blockages. The paper shows that a model of the level can be produced with sufficient accuracy to enable the detection of blockages, using the historical level and rainfall data to build the model. The output from the model can also be combined using simple error measures and a temporal threshold to define a variable which can be used for the accurate classification of the historical blockages which have occurred. The output from this has potential benefits to WaSCs in the understanding of asset performance, information for the management of alarms, and the automated provision of notifications when abnormal behaviour occurs, typical of a blockage event. Further work will include the extension of this work to other sites, and the potential applications of more sophisticated classification techniques.

6. Acknowledgements

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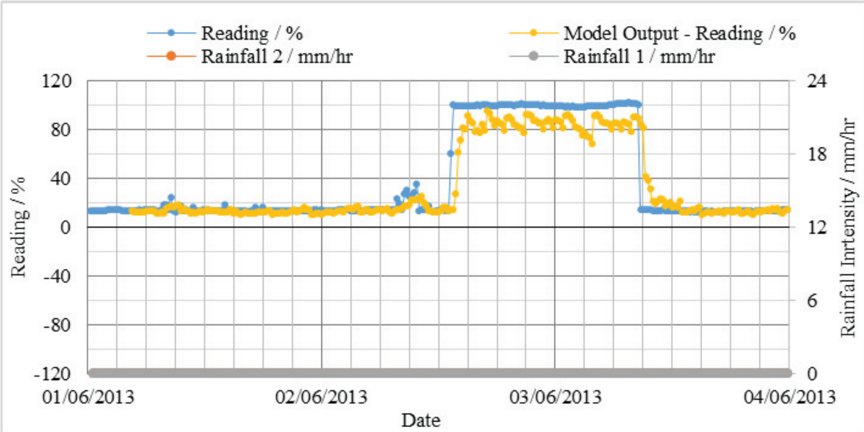
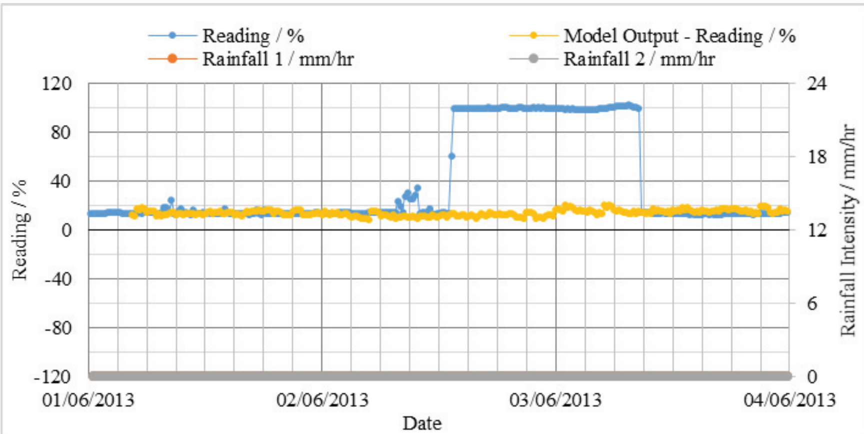
Appendix A. Appendix



(a)

Figure 3: these charts show the telemetry trends for a blockage event which occurred. The charts show the actual and predicted readings, along with the rainfall intensity. (a) shows the results for model 1 and (b) for model 2.



(b)