Near Real-Time Detection of Blockages in Wastewater Systems using Evolutionary Artificial Neural Networks and Statistical Process Control

Détection en Temps Réel Des Blocages Dans Les Systèmes D'assainissement Intelligents

T. Rosin[1,2], M. Romano[2], E. Keedwell[1], Z. Kapelan[1,3]

[1]Centre for Water Systems, College of Engineering, Mathematics and Physical Sciences, University of Exeter, Exeter, EX4 4QF, UK
[2]United Utilities Plc, Lingley Mere Business Park, Warrington, WA5 3LP, UK
[3]Delft University of Technology, Department of Water Management, Stevinweg 1, 2628 CN Delft, The Netherlands
Corresponding author:talia.rosin@uuplc.co.uk

RÉSUMÉ

Les bouchons d'égouts constituent un problème de taille pour les services de traitement des eaux usées pouvant entrainer perte de service, pollution de l'environnement et d'importants couts opérationnels. La collecte de données générées par les systèmes de télémétrie installés dans les égouts offre la possibilité de modéliser en temps réel ces réseaux unitaires d'assainissement. Cette étude présente une nouvelle méthode utilisant des prédictions évolutives des niveaux des réseaux unitaires d'assainissement et un modèle statistique pour détecter des bouchons en temps réel. Cette méthode a été appliquée avec succès sur une étude de cas et a démontré son habilité à détecter des bouchons rapidement sans générer de fausse alerte.

ABSTRACT

Blockages are a major issue for wastewater utilities, causing loss of service, environmental pollution and significant clean-up costs. Increasing telemetry in Combined Sewer Overflows (CSOs) provides the opportunity for near real-time data-driven modelling of wastewater networks. A novel methodology has been developed and presented in this paper to detect blockage events at, or in the proximity of, a CSO in near real-time. The methodology utilises Evolutionary Artificial Neural Network (EANN) predictions of level in CSO chambers and Statistical Process Control (SPC). The methodology has been applied to a case study using data from a real CSO in the UK and is demonstrated to detect a blockage event quickly, whilst raising no false alarms.

KEYWORDS

Blockage Detection, Combined Sewer Overflow, Evolutionary Artificial Neural Network, Radar Rainfall Nowcasts, Statistical Process Control

1 INTRODUCTION

The detection and management of sewer blockages is an important consideration for wastewater utilities. Blockages are responsible for the majority of service interruptions and flooding incidents which occur in the sewer network and can cause a number of detrimental effects, including significant environmental pollution, damage to nearby properties and risks to public health. There are approximately 300,000 sewer blockages in the UK every year, resulting in costs of £100 million. With deteriorating sewer networks and increased water efficiency the number of blockages occurring on public sewer networks has been increasing in recent years.

Historically, wastewater utilities have relied on customer reports of blockage events, employing a reactive repair and maintenance approach. However, this results in increased loss of service and customer complaints, in turn affecting regulatory performance. A number of hardware-based techniques are employed for blockage detection; CCTV is the current industry standard. However, these techniques are often slow, expensive and labour intensive. There is therefore a need for fast and reliable blockage detection techniques, designed to operate in near real-time, so that proactive maintenance may be implemented.

Due to the Event Duration Monitoring requirements introduced by the Environment Agency, level monitoring will be required at the majority of Combined Sewer Overflows (CSOs) in England and Wales by 2020. Water utilities have thus begun installing large quantities of increasingly accurate level sensors in their networks, routinely collecting large volumes of sewer level data in near real time. This detailed data provides opportunities for in-depth analysis and modelling of the wastewater systems.

The objective of the work presented here is to describe a novel methodology utilising Evolutionary Artificial Neural Network (EANN) CSO level prediction and Statistical Process Control (SPC) to detect blockage events in near real-time. The methodology is applied to a case study site and is demonstrated to detect the occurrence of a blockage event quickly, with no false alarms raised.

2 METHODOLOGY

During the last two decades a number of methods based on artificial intelligence and statistical analysis have been successfully applied to fault detection and diagnosis. In the water industry this has frequently focused on the detection of pipe bursts in water networks through pressure/flow analysis (Romano, 2014; Mounce, 2010, Palau, 2012). However, a number of studies have also successfully applied advanced analytics techniques such as Artificial Neural Networks (ANNs) to CSO level forecasting and spill prediction (Rosin, 2017, 2018; Mounce, 2014; Fernando, 2016)

The novel detection methodology presented in this paper utilises an EANN model to generate short-term CSO level forecasts assuming normal conditions. The occurrence of a blockage in the proximity of a CSO causes the level in the chamber to behave abnormally, resulting in discrepancies between the actual sensor measurements and those predicted by the EANN model. SPC principles are then used to monitor these discrepancies and infer the occurrence of a blockage event. Bearing this in mind, the following two sub-sections provide further details of the EANN model and SPC principles utilised within the novel methodology, respectively.

2.1 EANN Model

The methodology presented here uses the EANN model developed by Rosin et al (Rosin, 2018). Here the EANN model is used to generate short term predictions (i.e. 15 minutes ahead) of CSO levels, assuming that no blockage has occurred. EANNs are a biologically inspired hybrid computational model which use Evolutionary Algorithms in conjunction with ANNs. An evolutionary optimisation strategy (Schwefel, 1995), inspired by the process of natural selection, automatically selects the optimal (i.e. that yields the best forecasting performance) ANN input structure and parameter set.

The EANN model takes as inputs a lag of past CSO chamber level data, observed rainfall data and forecast rainfall data. The model is composed of a feed forward ANN with a hyperbolic tangent transfer function for the neuron in the single hidden layer and a linear transfer function for the neuron in the output layer. The model is trained using 40% of an available historical dataset by means of the Back Propagation method (Rumelhart, 1986). The trained EANN model is then tested using a further 20% of the historical dataset. Finally, as will be explained further in the next sub-section, the remaining 40% of the historical dataset is fed to the trained and tested EANN model in a simulated online fashion (i.e. as the system would operate in real time) to enable the computation and selection/calibration of the various parameters of the control chart/run rules.

The above EANN model has been demonstrated to produce results superior to an ANN developed manually through trial and error whilst also requiring far less human time and effort for its development (Rosin, 2018). The use of an EANN model also makes the overall methodological framework more generic as the EANN model can be seamlessly applied to different CSOs/catchments. Furthermore, it is advantageous to use an EANN model for this specific application because of the large amount of data available and the large number of assets which require monitoring. Indeed, EANNs are data-driven and self-learning, in contrast to physically based models (traditionally used by utilities for sewer modelling) which are generally difficult to build and calibrate and are often computationally expensive.

2.2 Statistical Process Control

SPC-based control charts with run rules are used in the novel methodology presented here to: i) monitor the discrepancies between the actual sensor measurements and those predicted by the EANN model and ii) infer the occurrence of a blockage event.

SPC applies statistical analysis to measure, monitor and control processes and is widely used for fault detection and diagnosis (Shewhart, 1931). Control charts are one of the most prominent SPC techniques. The control charts utilise control limits which determine if, statistically, a process is behaving as expected or is ‘out of control’, i.e. a fault has occurred. Standard control charts are very efficient at detecting large and fast deviations from the process average, however they are generally insensitive to gradual and small changes. Therefore, run rules such as the Western Electric control rules (Western Electric Company, 1958) are often used to enhance the sensitivity and effectiveness (i.e. minimise false alarms) of the control chart. Run rules require a number of consecutive timesteps with abnormal values before an alarm is raised and, hence, effectively enable tight control limits to be used.
In this study, blockages are detected by monitoring the EANN model predictions-observed measurements discrepancies, $x_{EANN,t}$ - $x_{obs,t}$, where $x_{obs,t}$ is the observed sensor level at time t and $x_{EANN,t}$ is the EANN model prediction at time t. The control chart limits are defined as $L_i = \mu_{EANN,ts} + M_i{*}\sigma_{ts}$, where $\mu_{EANN,ts}$ and σ_{ts} are the mean and the standard deviation of the model discrepancies and M_i is a multiplier to be determined for each run rule, i. $\mu_{EANN,ts}$ and σ_{ts} are computed using the data in the last 40% of the historical dataset (see previous sub-section) and the relevant “historical” EANN forecasts. A modified set of the Western Electric control rules is used here. This rule set was identified and the relative M_i parameters were tested/calibrated following a sensitivity type analysis on a number of different, real-life CSO sites (8 different sites used in this study). Rules and M_i parameters which raised a low number of false alerts whilst still maintaining a fast detection time were selected. The selected run rules and M_i parameters are then applied at each timestep in near real-time. If a discrepancy falls outside the limit and any of the run rules are satisfied, the presence of a blockage is inferred and an alarm is raised.

3 CASE STUDY AND RESULTS

The blockage detection methodology described in the previous section was tested on an urban CSO in the United Utilities (one of the largest UK water and wastewater companies, located in the Northwest of England) network. A blockage occurred downstream of this CSO in July 2017, causing a rapid increase in sewer level (see Figure 1). The CSO began to overflow 3 days after the blockage started, and subsequently spilled continuously until it was removed by United Utilities personnel 3 days later. The blockage, therefore, caused an unconsented spill which could result in a fine from the regulator. Investigation during removal of the blockage by United Utilities personnel determined that it was caused by a build-up of siltation in the sewer pipe just downstream the CSO.

CSO level data, observed rainfall data and forecast rainfall data were obtained from April 2016 to August 2017. Six months of data (July 2016 – December 2016) were used for training and testing of the EANN model. CSO level forecasts were then generated for the remaining 11 months of data. For the blockage detection system, 4 months of this data (December 2016 – April 2017) was used for calculation of the control chart’s mean and standard deviation of the discrepancies. The blockage detection methodology was applied to the remaining 5 months of (unseen) data (April 2017 – August 2017). Although historical data was also used for the near real-time blockage detection analysis during April 2017 – August 2017, it is important to stress that measurements were fed in a simulated online fashion, i.e. as the system would operate in real time.
Analysis of the EANN forecasts demonstrates that the model is accurate, with a Nash-Sutcliffe index of 0.92. Figure 1 presents the results obtained by the detection system during the blockage event. The red vertical line indicates the first timesteps the blockage was detected and an alarm raised. It can be seen that the blockage was detected relatively quickly, 17 hours after the event start, i.e. 5.5 days before the

blockage was removed. Over the 5 months the methodology was run no false alarms were raised. The methodology is demonstrated, therefore, to be able to detect the blockage event in a timely manner. If employed by the wastewater utility the methodology would have alerted the company to the occurrence of a blockage 2.5 days before it caused an unconsented overflow which might have been sufficient to remove the blockage and prevent the CSO spill.

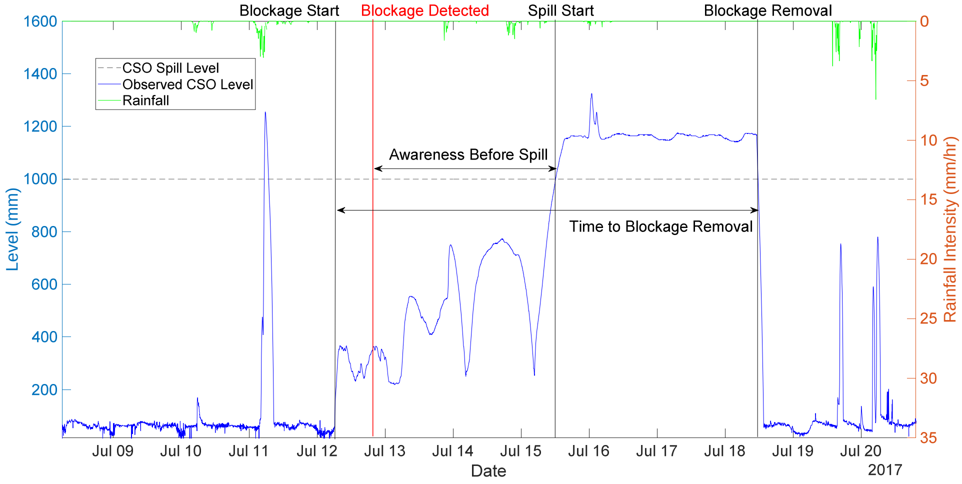

Figure 1 Results obtained by the detection system during a blockage event

4 SUMMARY

A novel methodology has been presented which is designed to detect blockage events in near real-time. The proposed methodology uses an EANN model to generate short term CSO level predictions. Discrepancies between level sensor measurements and the EANN model outputs are monitored using an SPC control chart with run rules, which infers the occurrence of a blockage. The system has been tested on a case study using data from a real CSO in the UK and was demonstrated to detect a blockage event in a timely manner without producing false alarms. Future work will investigate tailoring control chart limits for dry weather and for different rainfall events in order to decrease the blockage detection time. It is envisioned that the methodology will be beneficial to water and wastewater utilities, providing automated near real-time alarms and allowing proactive management of blockage events in the proximity of CSOs.

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