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CENTAUR: Real time flow control system for flood risk reduction

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Abstract

The effects of climate change and urbanisation are putting increasing pressure on wastewater networks both in the UK and overseas. In many cases there is a desire to avoid the high capital expenditure required to increase capacity in order to reduce flood events and CSO spills. Thus, innovative solutions to optimise the usage of existing capacity in sewer networks are an attractive proposition.

A novel Fuzzy Logic algorithm to operate a modified commercially available flow control device to allow unused capacity in the upper part of the wastewater network to be utilised in order to decrease flood volumes has been developed. This paper outlines the control concepts and presents a methodology and results from 'virtual testing' using a modified hydrodynamic network model linked to a Fuzzy Logic control algorithm in Matlab.

Introduction

The pressure on wastewater networks has grown in recent years due to the effects of climate change and increased urbanisation. This dual effect means that the capacity of networks to cope with runoff at the required rate often falls short of requirements leading to localised floods and/or increased CSO spills to receiving waters.

Climate change is likely to result in more intense storms. Equally, increased urbanisation means increased volumes of runoff to be conveyed by the same downstream infrastructure to the wastewater treatment works. The response to new requirements brought about by these pressures has often been capital solutions such as storage tanks, or an increase in the size of sewers. These solutions are disruptive and have associated costs often of many millions of pounds.

Capital solutions may no longer be viable, where private water companies have become too highly geared with debt, or in the aftermath of the global downturn. Additionally, there has been a movement toward smarter solutions which work existing assets harder; a realisation that capital solutions amount to the economics of conventional wisdom as opposed to innovation.

CENTAUR is a system designed to take advantage of the local untapped storage capacity in the upper parts of many networks thus attenuating the flow at flood-threatened downstream locations. The system uses a robust artificial intelligence routine based on Fuzzy Logic (FL), which processes local real-time in-sewer level information and reflects expert and local knowledge of network behaviour in order to be effective. Applied in the right setting, CENTAUR has the potential to deliver benefits equivalent to capital intensive solutions at significantly lower cost.

CENTAUR uses a novel FL algorithm to regulate the flow control device. This algorithm has been developed in Matlab (https://uk.mathworks.com/products/matlab/) and is not directly implementable in conventional sewer network modelling software. Thus, in order to test and refine the control system, 'virtual testing' has been carried out by linking Matlab to a SWMM hydrodynamic model (https://www.epa.gov/water-research/storm-water-management-model-swmm) of a test network to provide the input data and model the effect of the flow control device.

Outline of control system

The primary goal of the Fuzzy Logic algorithm is to operate the flow control device in order to utilise the capacity in the upstream sewer system and hence control the water level at a potential downstream flooding location. Thus, the risk of localised flooding can be reduced. The FL input parameters are derived from the water level in different sewer locations, while the output parameter is the setting of the flow control device. The flow control device used in this study is electrically activated. Developing a robust FL system necessitates the understanding of the control mechanism's impact on the water levels in the network.

Fuzzy Logic (FL)

Fuzzy systems are based on linguistic, imprecise approaches to describing complex systems. They don't demand knowledge of mathematical modelling. Each membership function imitates a linguistic approach which is used to describe some condition in every day descriptive usage (high, low, etc.). The rule set is based on fuzzy reasoning which employs linguistic rules in the form of IF {condition} – THEN {action} statements. There is a relationship between membership functions and rule sets. The membership values control the degree to which each of the IF – THEN rules will 'fire'.

Fuzzy Logic and fuzzy control feature a simplification of a control methodology description. This allows the application of 'human language' to describe the problems and their 'fuzzy' solutions. In many control applications the model of the system is unknown or the input parameters are highly variable and unstable. In such cases, fuzzy controllers, which are more flexible than traditional PID controllers, can be applied. It is also easier to understand and modify fuzzy controller rules, which not only use a human operator's strategy but are expressed in natural linguistic terms.

FL is particularly suited to wastewater applications, where phenomena can be understood but where their behaviour are characterised by variability. FL algorithms can capture, for example, expert knowledge, the conclusions of laboratory and field experiments, and modelling outputs around a particular phenomenon, and cope with their variability.

In wastewater, FL has been used in: detection (e.g. blockage detection; state detection in anaerobic wastewater treatment (Murnleitner et al., 2002); CSO performance optimisation and management in near-real-time (Mounce et al., 2014)) and control applications (e.g. pump station control and optimisation of energy use (Ostojin et al., 2011); control of additives in treatment; control of an activated sludge plant; energy saving in the aeration process (Ferrer et al., 1998); in-line control of non-linear pH neutralization; optimisation of nitrogen removal and aeration energy consumption in wastewater treatment plants).

For this application the selection of the input variables has to be done such that the FL algorithm can control the flow control device in order to reduce downstream flood risk without causing any additional upstream flooding. The FL algorithm uses water level data provided by a sensing network as input data. An algorithmic strategy for 'defuzzification' is applied to obtain a single-valued output.

Fuzzy controller performance is determined by its control rules and membership functions. For this reason it is very important to adjust these parameters around the controlled process. The generation of membership functions used in this paper has been achieved by expert judgement or by trial and error, but in later work optimisation of the membership functions (using evolutionary techniques) will be explored for specific sites.

Modelling Methodology

In order to develop and test the control system it was necessary to carry out 'virtual testing' using a hydrodynamic sewer network model where the movement of the flow control device can be controlled using the Fuzzy Logic scripts developed in Matlab. Most commercially available sewer modelling software does not have a documented facility that allows this. However SWMM (https://www.epa.gov/water-research/storm-water-management-model-swmm) being an open source software makes it possible due to third party add-ons. Riaño Briceño et al. (2016) have developed an interface (API) 'MatSWMM' (https://github.com/water-systems/MatSWMM) which allows a SWMM simulation to be started and controlled from Matlab, Python or LabView. This is clearly useful here to allow the Matlab based FL control to be applied, but could also be useful for batch running and automatically changing parameters when investigating, for example, uncertainty.

For the initial virtual testing, a section of an InfoWorks CS sewer network model which incorporates a known flood location has been extracted and exported to SWMM. In order to minimise run times and re-calibration, the model was cut at appropriate locations both downstream and upstream of the point of interest. Flows from the upstream sub-catchments were generated in InfoWorks and saved as time series data to be input to the SWMM model as an inflow. Prior to carrying out virtual testing, it is necessary to adjust and calibrate the network model in SWMM. This includes adding rain gauges, setting up dry weather flow parameters and adjusting runoff model parameters. Once this is completed it is beneficial to set up a hot start file which removes initial instabilities in the model run.

Figure 1 shows a flow chart of the virtual testing explaining the steps taken in the virtual testing procedure. The MatSWMM API can be set to run SWMM one time step at a time, reporting the results back after each step. The data is captured at a pre-defined time step and the FL code run at this time step. The FL determines whether the flow control device opening should be adjusted and the MatSWMM API feeds the amount by which the flow control should be adjusted back into SWMM hence manifesting an adaptive feedback loop.

Figure 2 shows the key parts of the test network, the node '1_Inflow' has inputs from the upstream network and the pipe '1_Inflow.1' provides storage upstream of the flow control which is the link '2_FCD.1'. The other key node in the system is '6_FloodLoc' which is known to flood regularly.

The results presented in this paper are from two FEH (Flood Estimation Handbook) design rainfall events with a summer profile, these are the M1-30 (1 year return period, 30 minute duration) and M5-120 to represent a range of the events which result in flooding. Time series rainfall incorporating multi-peaked events will also be used in testing, but these results are not included here.

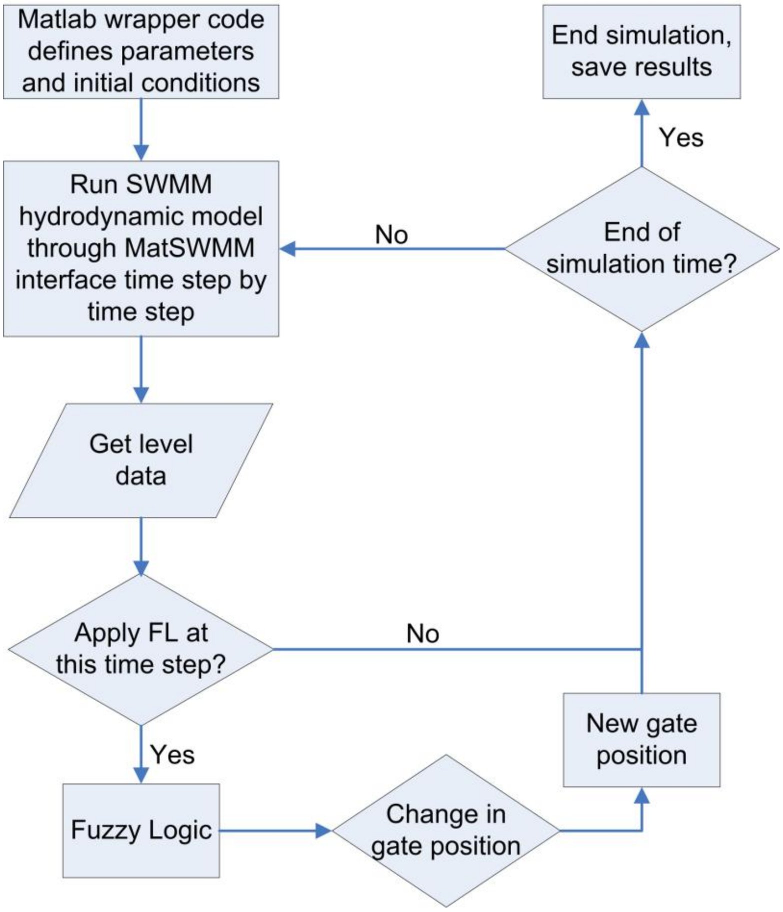

Figure 1: Flow chart showing the 'virtual testing' process.

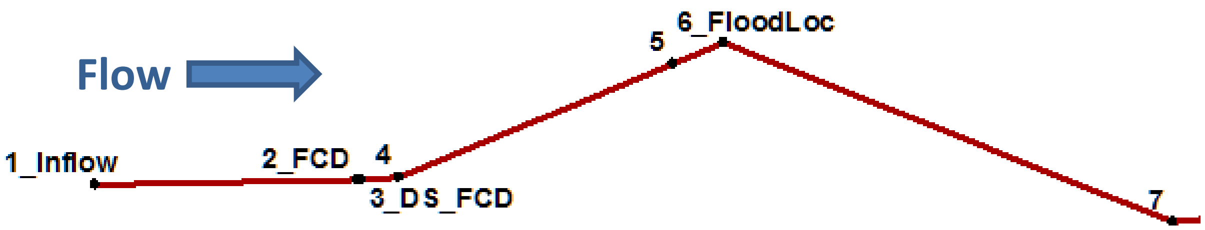

Figure 2: Plan of test network.

Results and Discussion

Figure 3 shows the water depths modelled at the flooding node (blue) and at the node immediately upstream of the flow control (red), alongside the rainfall intensity (purple) for the M1-30 event when the flow control is not used. A water depth of 100% represents the depth just prior to the onset of flooding, hence it can be seen that the event results in flooding for a period of just over 40 minutes and results in a total flood volume of 47 m^3. Figure 4 shows the same rainfall event but with the FL flow control activated, instead of plotting the rainfall intensity, the flow control position is plotted in green. The FL flow control reduces the total flood volume by 26 m^3 and the duration of flooding to 12 minutes. Clearly there could be potential to further optimise this by closing the flow control more quickly and also opening it sooner after the event as the stored volume continues to increase after the rainfall event has passed. However, the FL control does release the stored volume in a controlled manner. For the M5-120 event, the uncontrolled flood volume is 247 m^3 and duration is 4hrs 50 minutes. With the FL flow control the flood volume reduces to 113 m^3 and the duration to 3 hours.

For the shorter, high intensity event, the current limitation on reducing flooding is the rate at which the upstream storage can be activated, which is primarily a function of the FL control algorithm, rather than mechanical limitation of the device. Considering the longer, lower intensity event the limitation is the available volume in the upstream pipe which becomes full about 50 minutes after the flow control first activates.

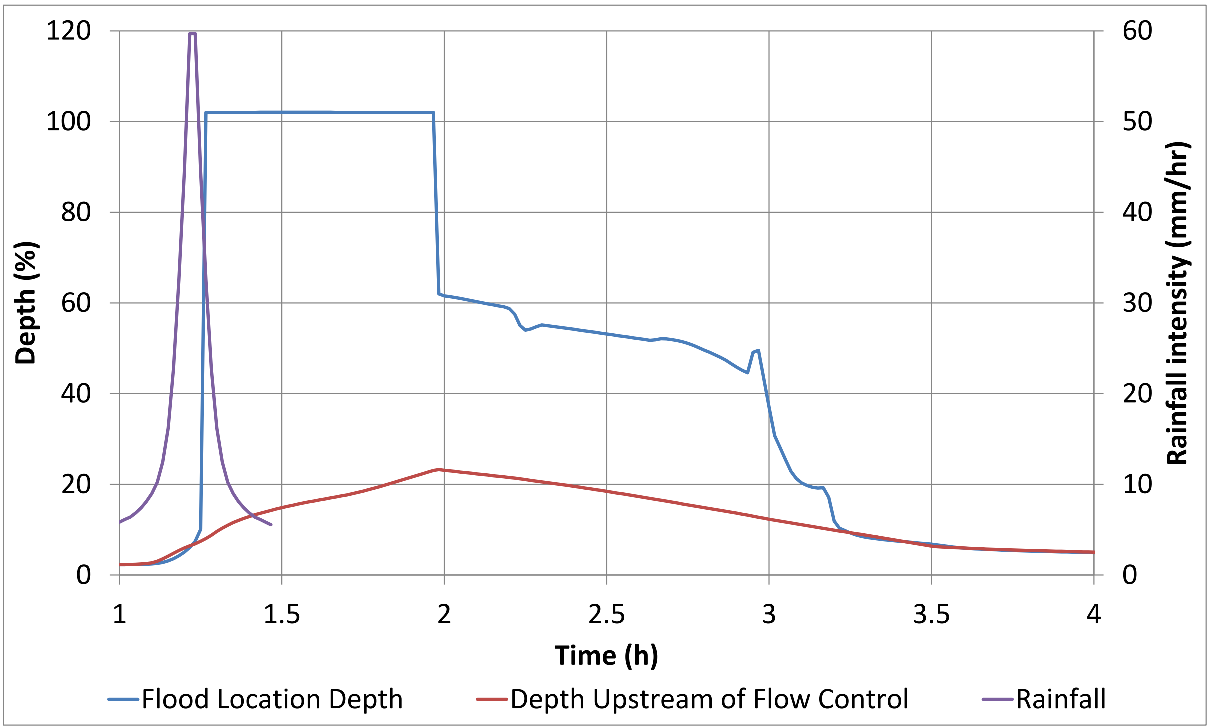

Figure 3: Results for M1-30 event without use of flow control.

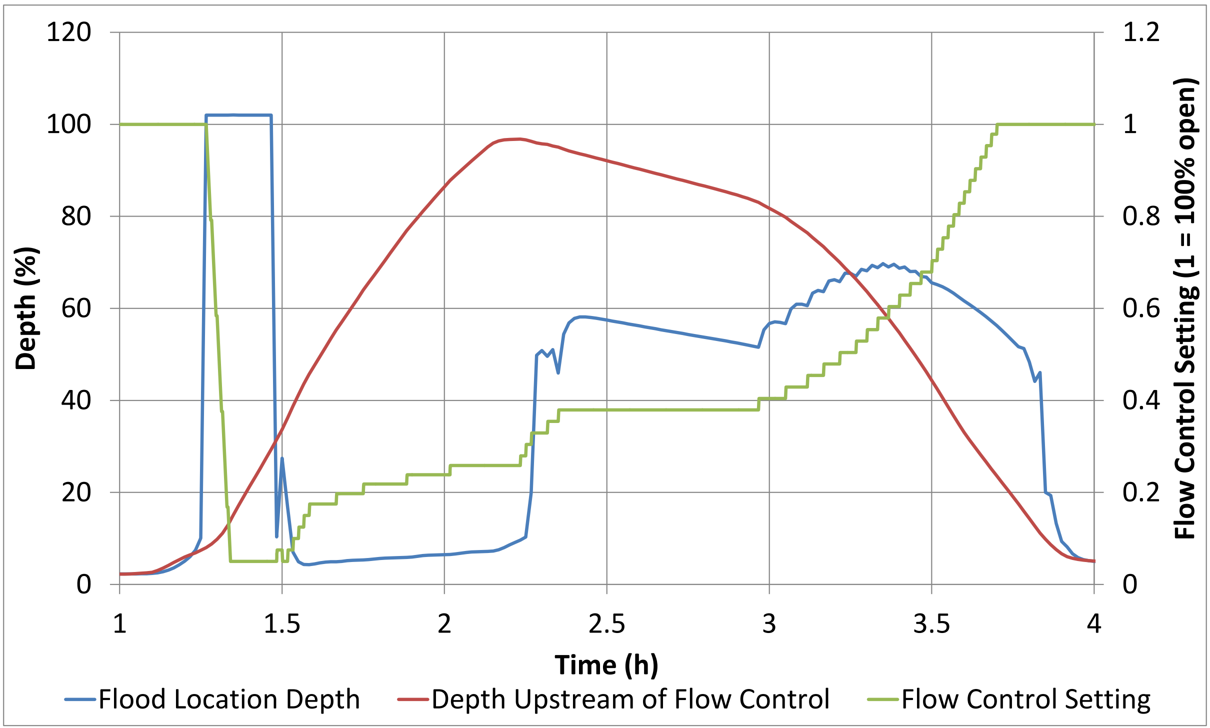

Figure 4: Results for M1-30 event with use of FL flow control.

Conclusions and next steps

The paper shows the successful use of the MatSWMM API to develop and show the potential benefits of a Fuzzy Logic driven flow control device to reduce flood volumes in wastewater networks.

The system is currently undergoing testing in a full scale laboratory facility at the University of Sheffield and will be installed into a live wastewater network in Coimbra, Portugal before the end of 2016.

A further step to optimise the Fuzzy Logic membership functions is being developed. This optimisation will allow the algorithm to be tuned for different networks and can also provide a better understanding of the sensitivity and useful range of these parameters. This will be carried out using a Genetic Algorithm.

Further Information

Additional information on the CENTAUR project is available at www.shef.ac.uk/centaur.

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References

Ferrer, J., Rodrigo, M. A., Seco, A., & Penya-Roja, J. M. (1998). Energy saving in the aeration process by fuzzy logic control. *Water Science and Technology*, 38(3), pp. 209–217.

Mounce, S. R., Shepherd, W., Sailor, G., Shucksmith, J. and Saul, A. J. (2014). Predicting CSO chamber depth using Artificial Neural Networks with rainfall radar data. *IWA Water Science and Technology*. 69(6), pp. 1326-1333

Murnleitner, E., Becker, T. M., & Delgado, A., (2002). State detection and control of overloads in the anaerobic wastewater treatment using fuzzy logic. *Water Research*, 36(1), pp. 201–211.

Ostojin, S., Mounce, S. R. and Boxall, J. B. (2011). An artificial intelligence approach for optimising pumping in sewer systems. *Journal of HydroInformatics*, 13 (3), pp. 295-306.

Riaño-Briceño, G., Barreiro-Gomez, J., Ramirez-Jaime, A., Quijano, N. Ocampo-Martinez, C., (2016). MatSWMM – An open-source toolbox for designing real-time control of urban drainage systems, *Environmental Modelling & Software*, 83, DOI: 10.1016/j.envsoft.2016.05.009.

Zadeh, L. A. (1968). Fuzzy algorithms. *Information and Control*, 12, pp. 94-102.