Risk-based Water Quality Management in an Integrated Urban Wastewater System under Climate Change and Urbanisation

Maryam Astaraie-Imani[a]; Zoran Kapelan[b]; David Butler[c]
Centre for Water Systems (CWS),College of Engineering, Mathematics and Physical Sciences (CEMPS), North Park Road, University of Exeter, Exeter EX4 4QF, Devon, United Kingdom
ma353@exeter.ac.uk[a];Z.Kapelan@exeter.ac.uk[b]; D.Butler@exeter.ac.uk[c]

Abstract: Climate change and urbanisation are key factors potentially affecting the future of water quality and quantity in urbanised catchments and are associated with significant degrees of uncertainty. Maintaining or even improving urban recipient water quality under this uncertain future will be a major challenge. The study reported in this paper explores the potential for managing water quality within a novel risk-based framework in the context of an Integrated Urban Wastewater System (IUWS) comprised of a sewer system, wastewater treatment plant and the recipient. In the study, we explore the potential for managing water quality failure risk by optimising the operational control and/or design of the wastewater system. Water quality failure risk is defined as the product of the likelihood and impact of water quality standard breaches. The optimisation objectives are the minimisation of water quality failure risk in terms of both dissolved oxygen and ammonia concentrations. The decision variables are a set of IUWS operational control and design parameters. The above optimisation problem was solved using the modified MOGA-ANN method. The results obtained from a semi-hypothetical case-study undergoing urbanisation and subject to climate change indicate that operational control optimisation has the potential to reduce the risk of recipient water quality failure but, in this particular case, cannot fully meet appropriate water quality standards. It was found that an acceptable level of risk can only be achieved by combining improved operational control and system (re)design.

Keywords: Climate change, Integrated modelling, risk, uncertainty, optimisation, Urbanisation, Wastewater system, Water quality.

1. INTRODUCTION

There is an emerging consensus that progress towards more sustainable urban water and wastewater systems can only be achieved by considering future global changes (e.g. climate, population, anthropogenic activities) and explicitly recognising the associated risks and uncertainties [UNESCO, 2011]. Given the importance of water quality improvement and the urgent goal of reaching 'good ecological status' under the Water Framework Directive [CEC, 2000], more attention is being given to developing risk-based approaches to water quality management [McIntyre et al., 2003; Sarang et al., 2008]. There is also increasingly, awareness amongst decision-makers of the need to take risk-based approaches [Willows and Connell, 2003]. This study adds to the literature by focussing on how the urban wastewater system can be better designed and operated to reduce the risk of water quality failure all within the context of increasing uncertainty associated with climate change and on-going urbanisation.

2. RISK-BASED OPTIMISATION MODEL FORMULATION

This study investigates how the performance of an urban wastewater system can be improved to reduce water quality risk failure using two approaches: operational control only (i.e. operational control model) and redesigning only (i.e. design model). The outcome will be potential strategies (operational and/or design) required to reduce the risk of these under the future changes. Due to the time demanding optimisation process in this study, the meta-model "modified MOGA-ANN" developed by Astaraie-Imani et al. [2011a], is used to reduce the optimisation time.

Figure 1 shows the semi-real case study used here comprising a sewer subsystem, a wastewater treatment plant (WWTP) and a hypothetical river. This was originally defined by Schütze et al. [2002] and used by Butler and Schütze [2005] for real time control of the IUWS.
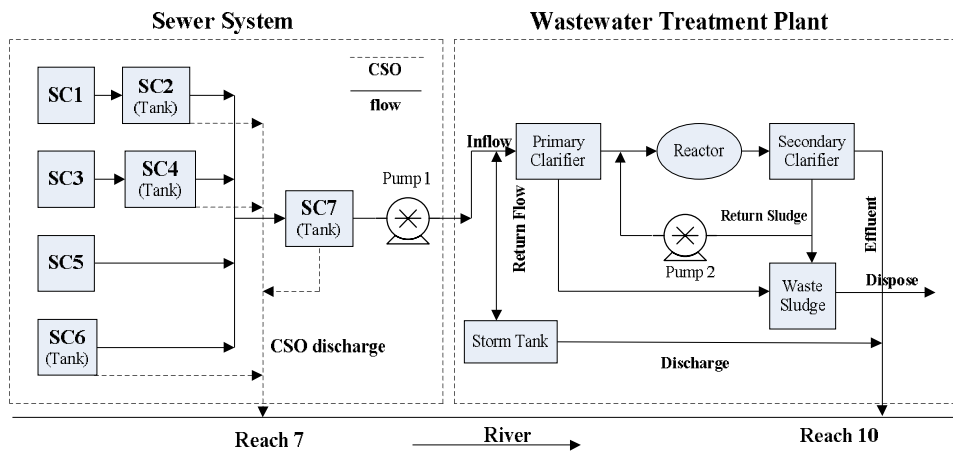

Figure 1 Schematic of the case study

2.1. Objectives

In this study, the risk-based model developed is formulated as a two-objective optimisation problem. For this purpose Dissolved Oxygen (DO) and un-ionised ammonia concentrations are selected for their importance to the health of aquatic life. The model objectives are:

- Minimise the risk of DO failure in the river;
- Minimise the risk of un-ionised ammonia failure in the river.

The above two risks are quantified using the following standard model:

Risk = Consequence × Probability (of water quality failure) (1)

2.1.1. Consequence

In the EA's report [2007] un-ionised ammonia is known to have long-term effects on the health of aquatic life, affecting emergence, hatching, growth but the largest effect is on mortality. Also fishes were considered as the most sensitive species of aquatic lives in this report. The test results in the aforementioned report are expressed as impacts of concentration lethal to 50% of the organisms (LC50). Therefore LC50 data for fish has been sourced [Environment Agency, 2007] for un-ionised ammonia. The empirical CDF curve of un-ionised ammonia concentrations has been produced from the associated LC50 data to show the consequence of un-ionised ammonia failure (see Figure 2). As it can be observed in Figure 2, the

normalised consequence of this failure is shown as a function of the logarithm of the un-ioinised ammonia concentration presented on the horizontal axis.

Zweig et al. [1999] reported the DO concentration tolerances for different aquatic species in the river. The aquaculture related information provided was used here to represent the consequence of the DO failure in the recipient and to, in turn, generate the empirical CDF curve. For this purpose the DO concentration values from Zweig et al. [1999]'s report were selected. Then these data were sorted in a descending order and the consequences of DO failure are estimated using the Weibull formula. Figure 3 shows the empirical CDF provided for DO failure with the normalised estimated consequences on the vertical axis.
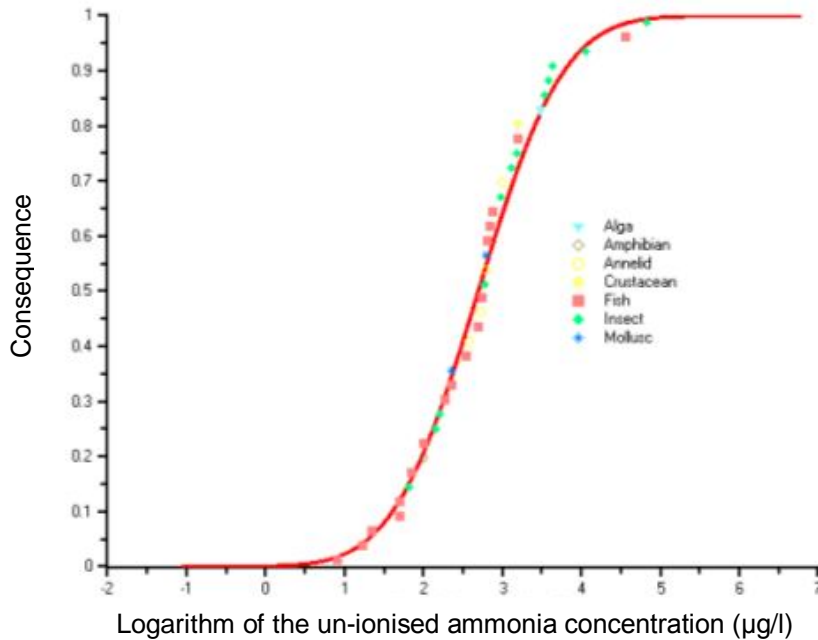

Figure 2 Empirical CDF of freshwater long term data for un-ionised ammonia concentration (µg/l) on fish mortality [EA, 2007]
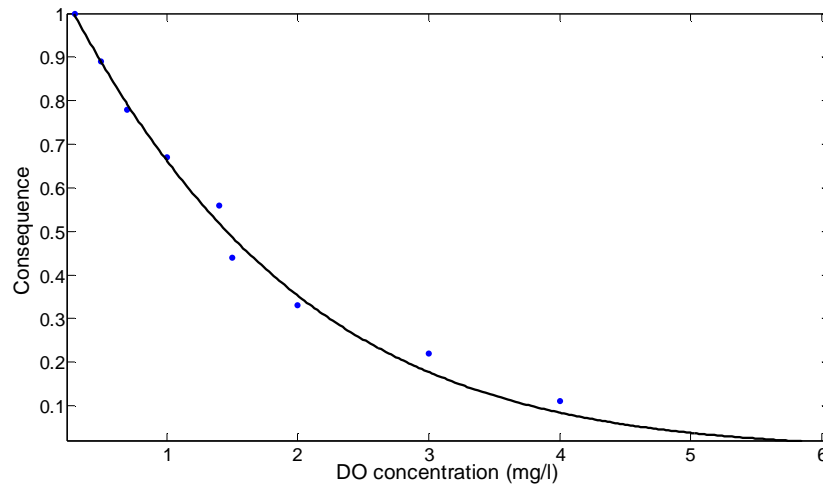

Figure 3 Empirical CDF of freshwater long term data for DO concentration (mg/l) on fish mortality

2.1.2. Probability of Water Quality Failure

The probability of water quality failure could be interpreted in a number of different ways, but as the aquatic life mortality is related to the "duration" and "frequency" of

poor water quality [FWR, 1994], the fraction of time that DO and un-ionised ammonia concentrations breach the 4 mg/l threshold should be a reasonable representation, as shown in the following equation:

$$Probability\ of\ failure = \frac{\sum Duration\ (DO < 4\frac{mg}{l}\ or\ un-ionised\ ammonia \geq 4\frac{mg}{l})}{Total\ simulation\ time} \qquad (2)$$

The above threshold value was selected based on the observations made in FWR [1998] report about the likely impact of DO and un-ionised ammonia concentrations on the mortality of aquatic life species.

2.2.   Climate Change and Urbanisation Parameters

Urbanisation can, in principle, be represented by a number of different parameters. In this study, the increase in population count over a given period of time, per capita water consumption rises and impervious surface increase (i.e. urban creep), have been used [Astaraie-Imani et al., 2011b]. Rainfall has been selected as the key indicator of climate change in this study considering its important impact on IUWS operational control and design. Future increases of rainfall depth (RD) and intensity (RI) in the UK [Hulme et al., 2002; IPCC, 2000; IPCC, 2007] have been used [Astaraie-Imani et al., 2011b].

Uncertainties in the input urbanisation parameters were generated using a Latin Hypercube Sampling approach. The sampling size for this purpose was 20 samples.

2.3.   Decision Variables

Table 1 shows the system operational control and design parameters used as the decision variables in the model (see section 2).

Table 1 Decision variables' nominal values and their value ranges

	parameters	Parameters description	Values/ value ranges in the	
			operational control	design
Operational control	Q_{maxout} (m³/d)	The maximum outflow rate of sewer system (ST_7)	[3,8] **	[2,9]**
	Q_{maxin} (m³/d)	The maximum inflow rate to the WWTP	[2,5]**	[2,5]**
	Q_{trigst} (m³/d)	The threshold triggering emptying the storm tank	[16416,31104]	[16416,31104]
	Q_{ST2} (m³/d)	Maximum outflow rate of ST_2	5*	[2,9] *
	Q_{ST4} (m³/d)	Maximum outflow rate of ST_4	5*	[2,9] *
	Q_{ST6} (m³/d)	Maximum outflow rate of ST_6	5*	[2,9]*
Design	a_2 (%)	Contribution-coefficient of ST_2	21.2 %	[0 %,100 %]
	a_4 (%)	Contribution-coefficient of ST_4	10.61 %	[0 %,100 %]
	a_6 (%)	Contribution-coefficient of ST_6	15.15 %	[0 %,100 %]
	a_7 (%)	Contribution-coefficient of ST_7	53.03 %	[0 %,100 %]

*These values are multiples of Dry Weather Flow (DWF) of their relevant sub-catchment area (see Figure 1).
**These values are multiples of the treatment capacity of the WWTP (27,500 m³).

2.3.1.   Decision Variables: Operational Control

A number of decision variables are currently built into the IUWS operational control model as follows:

- Q_{maxout}: This is the maximum outflow rate from the last storage tank in the sewer system. This operational control parameter controls combined sewer

overflow (CSO) discharges to the river and the wastewater inflow to the wastewater treatment plant.

- Q_{maxin}: This represents the maximum inflow to the wastewater treatment plant. It controls the inflows to the primary clarifiers while considering the capacity of the wastewater treatment plant and impacts the rate of the storm tank overflows into the river.
- Q_{trigst}: This defines the threshold at which the storm tank is triggered to be emptied. This parameter can control the operational control of the storm tank not to overflow to the river.

The other operational control parameters in Table 1 (i.e. Q_{ST2}, Q_{ST4} and Q_{ST6}) are set to their nominal values [Butler and Schütze, 2005; Fu et al., 2009].

2.3.2. Decision Variables: Design

The operational control and design parameters as the decision variables of the design model have also been incorporated in Table 1.

Note that the additional storage required is used as a surrogate for the corresponding capital cost. The goal is to iteratively reduce the total IUWS redesign cost until the optimal Pareto fronts can meet a low risk level e.g. less than 1% in this study.

For the purpose of estimating the minimum storage capacity increase, the system storage capacity increment factor (c) is initially assumed. This factor upgrades the storage capacity of the catchment as shown in the following equation:

$$V_{new} = V(1 + c/100) \tag{3}$$

where, V_{new}: increased storage capacity of the catchment (m^3); V: current storage capacity of the whole catchment equal to 13,200 m^3. Then this factor is applied to the design optimisation model to achieve to the minimum storage capacity increase by repetitive optimisation processes. The minimum value of c obtained from the above is used to calculate the associated IUWS redesign costs.

Storage tank contribution-coefficient (a_2, a_4, a_6 and a_7)

The aforementioned minimum storage capacity increase obtained needs to be distributed among the existing storage tanks in the catchment by a storage tank contribution-coefficient and this is calculated according to the following equation:

$$ST_i = V_i + V_{new} \times a_i/100 \tag{4}$$

$$\sum a_i/100 = 1$$

where, ST_i: increased storage capacity of storage tank i (m^3); V_i: existing volume of storage tank i (m^3); i: storage tank index; V_{new}: increased storage capacity of the catchment (m^3); a_i: contribution-coefficient of storage tank i from the increased storage capacity of the catchment (%).

There is dependency between the performance of the storage tanks' capacities and their outflow rates [Fu et al., 2010]. Therefore if the storage tank's capacity changes (e.g. increases), its maximum outflow rate (throttle flow) needs to be adjusted accordingly. This provides the potential for more efficient usage of the storage tank capacity to reduce the CSOs. Therefore the values/value ranges of the maximum outflow rates from the storage tanks changed to the new value ranges (see Table 1).

The storage tank contribution coefficients are applied to each of the existing storage tanks in the case study (ST_2, ST_4, ST_6 and ST_7 shown in Figure 1), to derive the optimal contribution of each. These coefficients are considered as the

design optimisation model decision variables (see Table 1) and used as shown in equation (5):

$$ST_i = V_i + V \times a_i/100 \qquad\qquad\qquad (5)$$

where, ST_i: increased storage capacity of each storage tank (m^3); V: increased storage capacity of the catchment (m^3); i: storage tank index; a_i: contribution-coefficient of each storage tank (%).

Operational control parameters (Q_{ST2}, Q_{ST4} and Q_{ST6})

There is an interaction between the performance of the storage tanks' capacities and their maximum outflow rates [Fu et al., 2010]. Consequently when changing the capacity of the storage tanks, the maximum outflow rates (throttle flow) need to be adjusted. This provides the potential for more efficient usage of the redesigned storage capacities to reduce the risk of water quality failure. Therefore the value ranges of Q_{maxout}, Q_{ST2}, Q_{ST4} and Q_{ST6} need to change in the design model compared with the operational control model. Q_{maxin} and Q_{trigst} are considered with the same value ranges as the operational control model (see Table 1).

2.4.   Results and Discussion

Figures 4 and 5 show the optimal Pareto fronts obtained from the risk-based operational control and design optimisation models under the RD and RI scenarios. Risk values under the base case (BC) are also presented.

2.4.1.   Results and Discussion of the Operational Control Optimisation Model

It can be observed in Figure 4 and Figure 5 that the risk values in the IUWS under the base case conditions was reduced. Also the risk values under the RD scenario are greater than for RI scenario and these risk values for DO failure are more critical than for un-ionised ammonia. The reasons are prompted by the greater volume of wastewater generated under the RD scenario which increases the potential for combined sewer overflow discharges into the river. As a result, under the future climate change and urbanisation uncertainties, additional strategies are required to reduce the risk of failures near to a very low risk or even non risk values.

2.4.2.   Results and Discussion of the Design Optimisation Model

Using the iterative procedure mentioned in section 2.3.2, the minimum storage capacity increases required under the RD and RI scenarios were estimated as being approximately 200% and 150% respectively. It can be observed in Figure 4 and Figure 5 that these values are good enough to control and reduce the CSOs in the IUWS. In other words, the design optimisation model developed has the potential to reduce the risk of water quality failures significantly (in comparison with the operational control optimisation model) as it can get near the low risk values or zero risk.
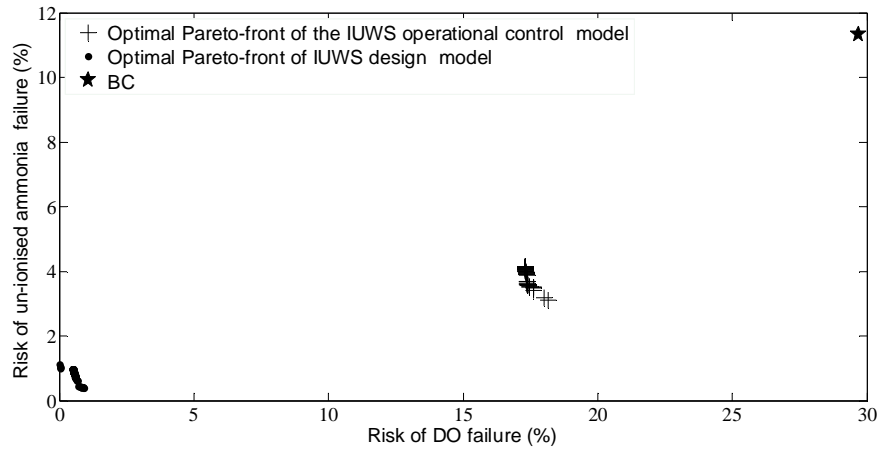
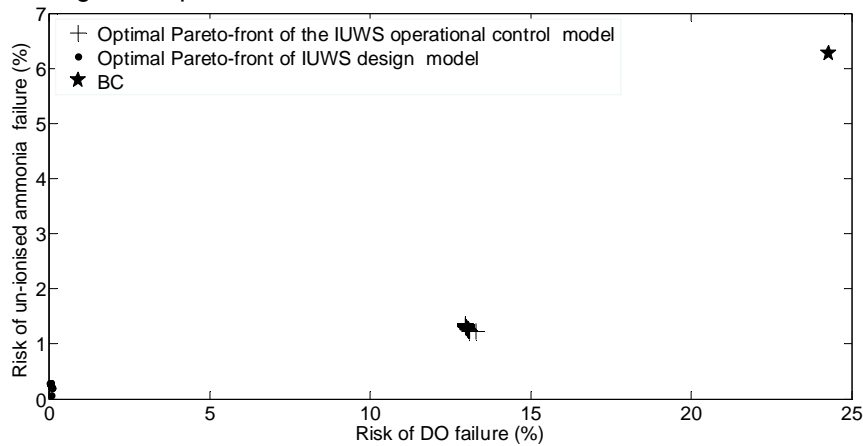Figure 4 Optimal Pareto fronts of the risk-based model under RD

Figure 5 Optimal Pareto fronts of the risk-based model under RI

3. CONCLUSIONS AND RECCOMMENDATIONS

In this study, the performance of an urban wastewater system was evaluated to discover if it could be operated or redesigned to reduce the risk of river water quality failure. The main findings are:

- Uncertainty in the urbanisation parameters under the RD scenario brings about a greater risk of water quality failure (DO and un-ionised ammonia failures) than under the RI scenario.
- The climate change and urbanisation in the case study analysed here have more significant effect on the risk of DO failure than the risk of un-ionised ammonia failure.
- Improving the operational control of the IUWS in isolation was not able to reduce the risk of water quality failures to meet the very low risk or zero risk in this study.
- Improving the design of the system (in addition to improved operational control) is effective to reach the very low risk or zero risk levels.
- Considering the risk of water quality failure as the optimisation objective instead of water quality parameter concentrations, could have considerable impact on redesign costs, and this deserves further investigation.

REFERENCES

Astaraie-Imani, M., Kapelan, Z., Fu, G. and Butler, D., MOGA-ANN based optimisation of integrated urban wastewater system control strategies, paper presented at Computing and Control for the Water Industry (CCWI) 11th International conference, Exeter, UK, September 5-7, 2011a.

Astaraie-Imani, M., Kapelan, Z., Fu, G. and Butler, D., Assessing the combined effects of urbanisation and climate change on the river water quality in an integrated urban wastewater system in the UK, *Journal of Environmental Management, 2011b* (Accepted).

Butler, D. and Schütze, M., Integrating simulation models with a view to optimal control of urban wastewater systems, *Environmental Modelling & Software*, 20, 415-426, 2005.

CEC (Council of the European Communities)*, Directive 2000/60/EC:* a framework for community action in the field of water policy, European Union, Luxembourg, October 23, 2000.

Environment Agency (EA), Proposed EQS for Water Framework Directive Annex VIII: substances: ammonia (un-ionised), Science Report SC040038/SR2, 2007.

Fu, G., Butler, D. and Khu, S.T., The impact of new developments on river water quality from an integrated system modelling perspective, *Science of the Total Environment* , 407, 1257–1267, 2009.

Fu, G., Khu, S. and Butler, D., Optimal distribution and control of storage tank to mitigate the impact of new developments on receiving water quality,*Jounral of Environmental Engineering*, 3, 136, 2010.

FWR, Urban pollution management manual, Foundation for Water Research. UK: Marlow, 1994.

FWR, Urban pollution management manual, Foundation for Water Research. FR/CL0009 2nd, UK: Marlow, 1998.

Hulme, M., Jenkins, G.J., Lu, X., Turnpenny, J.R., Mitchell, T.D., Jones, R.G., Lowe, J., Murphy, J.M., Hassell, D., Boorman, P., McDonald, R., Hill, S. , Climate Change Scenarios for the United Kingdom: The UKCIP02 Scientific Report, Tyndall Centre for Climate Change Research, School of Environmental Sciences, University of East Anglia, Norwich, UK, 120, 2002.

IPCC, Emission Scenarios: Special Report of Working Group III to the IPCC, Nakicenovic, Neboisa, Swart, Rob (Eds.), Cambridge University Press, UK, 570, 2000.

IPCC, Climate Change 2007: Synthesis Report, Group contributions to the Fourth Assessment Report, 2007.

McIntyre, N.R., Wagener, T., Wheater, H.S. and Chapra, S.C., Risk-based modelling of surface water quality: a case study of the Charles River, Massachusetts, *J. Hydrol.* , 274(1–4), 225–247, 2003.

Sarang, A., Vahedi, A. and Shamsai, A., How to Quantify Sustainable Development: A Risk-Based Approach to Water Quality Management, *Environmental Management*, 41, 200–220, 2008.

Schütze, M., Butler, D. and Beck, M.B., Modelling Simulation and Control of Urban Wastewater Systems, Springer, Berlin, 2002.

UNESCO, [Online] Available at: http://www.unesco-ihe.org/Research/Research-Themes/Urbanisation#2, 2011.

Willows, R.I. andConnell, R.K., Climate adaptation: risk,uncertainty and decision-making, UKCIP technical report, Oxford: UKCIP, 2003.

Zweig, R.D., Morton, J.D. and Stewart, M.M., Source Water Quality for Aquaculture-A Guide for Assessment, Washington, D.C.: The World Bank, 1999.