



COLLEGE OF ENGINEERING, MATHEMATICS AND PHYSICAL SCIENCES

Modelling the Performance of an Integrated Urban Wastewater System under Future Conditions

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ABSTRACT

The performance of the Integrated Urban Wastewater Systems (IUWS) including: sewer system, WWTP and river, in both operational control and design, under unavoidable future climate change and urbanisation is a concern for water engineers which still needs to be improved. Additionally, with regard to the recent attention around the world to the environment, the quality of water, as the main component of that, has received significant attention as it can have impacts on health of human life, aquatic life and so on. Hence, the necessity of improving systems performance under the future changes to maintain the quality of water is observed. The research presented in this thesis describes the development of risk-based and non-risk-based models to improve the operational control and design of the IUWS under future climate change and urbanisation aiming to maintain the quality of water in recipients.

In this thesis, impacts of climate change and urbanisation on the IUWS performance in terms of the receiving water quality was investigated. In the line with this, different indicators of climate change and urbanisation were selected for evaluation.

Also the performance of the IUWS under future climate change and urbanisation was improved by development of a novel non-risk-based operational control and design models aiming to maintain the quality of water in the river to meet the water quality standards in the recipient. This is initiated by applying a scenario-based approach to describe the possible features of future climate change and /or urbanisation.

Additionally the performance of the IUWS under future climate change and urbanisation was improved by development of a novel risk-based operational control and design models to reduce the risk of water quality failures to maintain the health of aquatic life. This is initiated by considering the uncertainties involved with the urbanisation parameters considered. The risk concept is applied to estimate the risk of water quality breaches for the aquatic life.

Also due to the complexity and time-demanding nature of the IUWS simulation models (which are called about the optimisation process), there is the concern about excessive running times in this study. The novel “MOGA-ANN β ” algorithm was developed for the optimisation process throughout the thesis to speed it up

while preserving the accuracy. The meta-model developed was tested and its performance was evaluated.

In this study, the results obtained from the impact analysis of the future climate change and urbanisation (on the performance of the IUWS) showed that the future conditions have potential to influence the performance of the IUWS in both quality and quantity of water. In line with this, selecting proper future conditions' parameters is important for the system impact analysis. Also the observations demonstrated that the system improvement is required under future conditions. In line with this, the results showed that both risk-based and non-risk-based operational control optimisation of the IUWS in isolation is not good enough to cope with the future conditions and therefore the IUWS design optimisation was carried out to improve the system performance. The risk-based design improvement of the IUWS in this study showed a better potential than the non-risk-based design improvement to meet all the water quality criteria considered in this study.

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LIST OF ABBREVIATIONS

AGA	Accelerating Genetic Algorithm
AMM	Ammonium
A-PIC	High-Performance Integrated Control
AR	Assessment Report
ASM	Activated Sludge Model
B	Behavioural
BC	Base Case
BOD	Biochemical Oxygen Demand
BSM	Benchmark Simulation Model
CC	Climate Change
CCU	Combined Climate Change and Urbanisation
CDF	Cumulative Distribution Function
Conc	Concentration
CSO	Combined Sewer Overflow
DO	Dissolved Oxygen
DSS	Decision Support System
DTM	Digital Terrain Model
DWF	Dry Weather Flow
EA	Environmental Assessment/Environment Agency
EIA	Environmental Impact Assessment
EQSs	Environmental Quality Standards
EU	European Union
FIS	Fundamental Intermittent Standards
FORA	First Order Reliability Analysis
FORM	First Order Reliability Method
FWLAM	Fuzzy Waste Load Allocation Model
GA	Genetic Algorithm
GB	Grey Box
GCM	General Circulation Model
GHG	Greenhouse Gas
GLUE	Generalised Likelihood Uncertainty Estimation
GSA	Global Sensitivity Analysis
IA	Impact assessment/ Impact Analysis

ICM	Integrated Catchment Modelling
ICS	Integrated Catchment Simulator
INCA	Integrated Catchment
IPCC	Intergovernmental Panel on Climate Change
IRA	Integrated Risk Assessment
IRIS	Integrated Risk Information System
IUWM	Integrated Urban Water Management
IUWS	Integrated Urban Wastewater Systems
IWWTS	Integrated WWTP-Sewer Systems
KS	Kolmogorov-Smirnov
LCA	Life Cycle Assessment
LCM	Land Change Modeller
LC50	Lethal to 50% of the organisms
LHS	Latin Hypercube Sampling
LoE	Lines of Evidence
LSA	Local Sensitivity Analysis
MC	Monte Carlo
NB	Non-Behavioural
NLP	Non-Linear Programming
ONS	Office for National Statistics
OPT	Optimisation
OWTS	Onsite Wastewater Treatment System
PCA	Pollution Control Agency
PDF	Probability Distribution Function
POMs	Programs of Measures
QUASAR	Quality Simulation Along River
RA	Risk Analysis/Assessment
RCM	Regional Climate Model
REW	Review Paper
RP	Return Period
RSA	Regional Sensitivity Analysis
RTC	Real Time Control
SA	Sensitivity Analysis
SRES	Special Report on Emission Scenario
SS	Suspended Solids

SWAT	Soil and Water Assessment Tool
SWMM	Storm Water Management
TGICA	Task Group on Data and Scenario Support for Impact and Climate Assessment
TUs	Treatment Units
UA	Uncertainty Analysis
UNEP	United Nations Environment Programme
UPM	Urban Pollution Management
Urb	Urbanisation
VSS	Volatile Suspended Solid
WaterRAT	Water quality Risk Analysis Tool
WFD(L)	Water Framework Directive (Legislations)
WGs	Working Groups
WMO	World Meteorological Organization
WQ	Water Quality assessment/management
WUs	Water-Using units
WWF	Wet Weather Flow
WWTP	Wastewater Treatment Plants

CHAPTER 1

INTRODUCION

1.1. General

Climate change and its effects are and will probably continue to be one of the major concerns that water engineers need to deal with throughout the world in this century. The main features of climate change are global warming, sea level rises, precipitation changes and ice cap melting. For example by the end of 21st century, average UK summer temperature is likely to rise by 3° C to 4°C, average summer rainfall across the UK may decrease by 11% to 27%, while winter is quite the inverse and the UK should expect significantly wetter winters. Sea levels are expected to rise and extreme weather events are likely to become more common (Hulme, *et al.*, 2002). Therefore it is obvious that climate change has significant potential to impact on urban environments and water infrastructure performance. Now, toward sustainable development in the water industry, water engineers have to consider these future climate changes in the design and management of water systems. Recent improvements in computational power and the coming into existence of tools for modelling future climate changes have provided the potential for water engineers to consider them in their designs and analysis.

Simultaneously with climate change, another concerning factor is the degree and rate of urbanisation. Multiple urbanisation stressors, including population growth, increased watershed imperviousness, destruction of the riparian vegetation, increased siltation, and changes in climate will impact water infrastructure in the coming century. These stress factors will alter the weather conditions, water temperature, water quality and quantity and consequently influence ecological processes and environment. Therefore these factors

require careful quantification and consideration by water engineers. There is a fact here that the changing climate arises from these anthropogenic activities while at the same time the climate change can have impact on human life. In other words these two factors are collated together. As a result, urbanisation can be measured by using different indicators, each of which has the potential to affect the water quality and/or quantity.

Urban wastewater systems are a part of the water systems in which the quality and quantity of water are affected by climate change and urbanisation. These systems are the collectors of surface runoff, dry weather flows from urban areas and their treatment in wastewater treatment plants (WWTP) followed by discharge to water recipients. In recent decades water planners have started to consider the impact of future changes on the design and operation of the water systems, but few studies have focused on these impacts on integrated urban wastewater systems (IUWS) including: sewer system, WWTP and river. Considering urban wastewater systems as integrated systems has the advantage of taking into consideration the interaction existing in the subsystems under these future changes. This can give a real estimation of the improvements required to cope with the future changes. Additionally, with regard to the recent attention around the world to the environment, the quality of water, as the main component of that, has received significant attention as it can have impacts on health of human life, aquatic life and so on. Hence, the necessity of improving systems performance under the future changes to maintain the quality of water is observed.

With regard to the importance of the environment in sustainable development, the quality of water can be an essential component of sustainable development. By now many studies have been performed to improve the design and operation of the IUWS with regard to the quantity of water. Having said this, fewer studies have focused on improving the systems' performance in terms of the quality of water in IUWS (see section 2.5 in Chapter 2). The operation of the IUWS is important and includes the performance of pumping stations in the sewer system and WWTP, aerators and other components of the system. The design of the IUWS can include several factors such as the size of the pipes in the sewer system, storage capacity of the sewer systems (e.g. storage tanks' volumes), storm tanks' capacities in the WWTP and volume of the reactors.

Improving the design of the IUWS has the potential to control and manage the quality and quantity of water in the system. They have an important role in controlling the Combined Sewer Overflows (CSOs) as the major source of pollution discharged in the rivers according to the findings in many studies. It needs to be noted that many studies have focused on improving the water quality in the recipient by applying surrogate objectives, but fewer have focused directly on the quality of water. Fortunately with improving computational power and new tools available to simulate urban wastewater systems as integrated entities, it is now easier to investigate their performance under the future changes and try to improve their design or operation under the future changes. Considering all this, it can be observed that the performance of the future IUWS requires optimisation, considering water quality indicators in addition to the water quantity.

1.2. Aim and Objectives

The overall aim of this PhD research work is to improve the operational control and design of the IUWS under future climate change and urbanisation aiming to maintain the quality of water in recipients. The aforementioned aim can be divided into the following specific objectives:

1. To investigate the impact of climate change and urbanisation on the IUWS performance in terms of the receiving water quality. In the line with this, different indicators of climate change and urbanisation are selected for evaluation.
2. To improve the performance of the IUWS (under future climate change and urbanisation) by improving the operational control of the IUWS aiming to maintain the quality of water in the river. This is initiated by applying a scenario-based approach to describe the possible features of future climate change and /or urbanisation.
3. To improve the performance of the IUWS (under the future climate change and urbanisation) by improving the design of the IUWS under the scenarios identified above (i.e. the scenarios where the operational control optimisation cannot meet the water quality standards in the recipient).
4. To improve the performance of the IUWS under future climate change and urbanisation by reducing the risk of water quality failures to maintain the health of aquatic life. This is initiated by considering the uncertainties involved with the urbanisation parameters considered. The risk concept is applied to estimate the risk of water quality breaches for the aquatic life.

1.3. Layout of the Thesis

This thesis is divided into eight chapters including this introductory chapter. In Chapter 2, firstly a review of the reports, papers and documents which can represent the future climate change and urbanisation is given. A review is made of the recent studies which have applied the integrated approach to investigate the impacts of future climate change and urbanisation on the urban wastewater systems performance. This is followed by reviewing studies on the future impacts of climate change and urbanisation on the IUWS performance. With regard to the uncertain nature of future projections, a review of sensitivity analysis, uncertainty analysis and risk analysis studies in the context of the IUWS are made afterwards. Finally, in the line with the aim of this study, a review made of the optimisation processes applied to urban wastewater systems to improve their performance to cope with the future changes is presented.

In Chapter 3, the methodology used to model the IUWS, together with the case study used throughout this thesis is introduced. Also the so called Base Case (BC) is introduced in this chapter and the performance of the model in terms of the water quality indicators is presented.

In Chapter 4, firstly a set of likely climate change, urbanisation and operational control parameters which have impacts on the quality of water in an IUWS are provided. This is followed by a review of two sensitivity analysis methods to identify the most effective input parameters to the IUWS model. After that, performance of the IUWS model with the selected input parameters are assessed in terms of the water quality parameters. At the end of this chapter the most significant input parameters in each group of climate change, urbanisation and operational control are identified and introduced.

In Chapter 5, firstly a scenario-based approach is applied to describe the possible features of future climate change and urbanisation and these features are considered as some scenarios. These provided scenarios are divided into two groups: climate change scenarios and combination of climate change with urbanisation scenarios. Then an operational control model is developed and applied to each scenario. This is followed by describing the meta-model “MOGA-ANN β ” algorithm for the optimisation process. The meta-model developed is tested and its performance is evaluated. Finally, a summary of the conclusions obtained from the operational control optimisation of the IUWS under the future changes is presented.

In Chapter 6, firstly a few scenarios are chosen with regard to the results achieved in Chapter 5. This is followed by development of a design optimisation model and application of the MOGA-ANN β algorithm for the optimisation process. After that, this model is applied to those critical scenarios to improve the performance of the system.

Finally, a summary of the conclusions obtained from the design optimisation of the IUWS under the future changes is presented and compared with the results of only operational control optimisation.

In Chapter 7, firstly the concept of risk of water quality failure is defined in the context of the IUWS. Then the aforementioned risk approach is used to develop a risk-based model in terms of water quality failure and applied to the IUWS optimisation model objectives to improve the performance of the IUWS accordingly. Then the uncertainties existing in the urbanisation parameters are considered to provide an operational control model with similar structure as in Chapter 5 and Chapter 6. The MOGA-ANN β algorithm is applied to improve the system performance and reduce the risk of water quality failures in the river under urbanisation uncertainty. This is followed by provision of a design model with similar structure as in Chapter 5 and Chapter 6, to improve the performance of the system under the urbanisation parameters' uncertainties. Finally, a summary of findings in this chapter is displayed.

In Chapter 8, a summary is made. After that, relevant conclusions obtained from the risk-based and non-risk-based operational control and design optimisation models under the future changes are described. This is followed by suggestions for future research work regarding the required solutions for engineers to adapt the IUWS to future changes.

CHAPTER 2

LITERATURE REVIEW

2.1. Introduction

This chapter reviews the literatures relevant to the impact of future climate change and urbanisation on the performance of the IUWS. Also it has a review on the studies about the improvement of the operational control and design of the IUWS under the future changes.

In section 2.2, a review is on the existing integrated approaches applied in modelling of the urban wastewater systems are presented. This is followed by explaining the advantages and impacts of such integrated approaches in different studies. Also the impacts of the IUWS on water quality in the water recipients are reviewed.

In section 2.3, a review on the recent studies about the possible future climate changes and their impacts on the IUWS performance is carried out. Also in this section a review on the future urbanisation impacts on the IUWS performance is presented. In these reviews different indicators of future climate change and urbanisation considered in water systems are introduced.

In section 2.4, a review on the impacts, sensitivities and risks analyses of water quality in the recipient in the IUWS under the future climate change and urbanisation is performed. Additionally in this section the water quality guidelines applied.

In section 2.5, with regard to the aim of this thesis, a review on the optimisation efforts to improve the IUWS performances is done. Additionally a review on

considering the risk and uncertainties impacts in improving the IUWS performance is performed.

Finally in section 2.6 a summary of the reviews done for this thesis in each section is presented and finally a brief view of the next chapter is displayed.

2.2. Integrated Urban Wastewater Systems Modelling

Rising standards of living and expectations for a better level of service, protection of the environment and approaching to sustainable systems, have increased the needs for more efficient urban wastewater systems. Meanwhile water quality has received significant attention and many guidelines have been developed all around the world to maintain and improve the quality of freshwaters (CEC, 2000; DAFF, 2000; SEPA, 1999).

It is argued that conventional approaches in urban wastewater system analysis which separate different components of the system to achieve proper performance practically cannot fully reach to the required efficiency. This can indicate the necessity of considering urban wastewater systems in an integrated frame to achieve the required water quality standards and provide the possibility of evaluating the systems' performance directly rather than referencing them to surrogate criteria. In recent years, newer integrated system modelling approaches/tools such as CITY DRAIN (Achleitner, *et al.*, 2007a) and Integrated Catchment Simulator (ICS) (Clifforde, *et al.*, 1999) have been developed which enable the interactions between the individual components to be dynamically represented. Integrated modelling approach can be applied in different studies such as water quality management, Real Time Control (RTC) of the urban wastewater system and impact assessment.

The European Union Water Framework Directive (WFD) is considered to be the key guiding framework for water quality management used in this study. Linking the integrated modelling approach with WFD water quality criteria can in principle lead to better water quality management. The aforementioned importance was investigated by Kallis & Butler (2001). They showed that the integrated analysis of urban wastewater systems is firmly in line with the precepts of the WFD. Also Vanrolleghem *et al.* (2005) applied an integrated modelling approach for urban wastewater system (including sewer system, WWTPs and river) to deal with the legislation about surface waters provided in

WFD in the EU. An integrated approach was adopted by Wilby *et al.* (2006a) for the impact assessment of the drainage network under climate change and land use change. This was performed by linking established models of regional climate (SDSM), water resources (CATCHMOD) and water quality (INCA) within a single framework. Kalavrouziotisa & Apostolopoulos (2007) applied an integrated approach in urban areas to reuse the treated wastewater effluents from WWTP. The integrated approach was successful in this study by providing the possibility of continuous monitoring a number of parameters concerned with the physical–chemical properties in the wastewater effluent. Vojinovic & Mark (2011) investigated the interaction between drainage system, WWTP and receiving water at Pattaya beach in the context of an integrated approach. This study aims to improve the quality of water in this area. In this study the MOUSE and MIKE21 tools were applied for the purpose of modelling and historical data were collected for calibration and validation of the model developed.

In line with the recent attention to the impact of future changes on the water quality, the integrated system modelling perspective was applied by Fu *et al.* (2009) to investigate the impact of new developments - as a ubiquitous feature of modern life - on river water quality in WWTP. The integrated model considered includes the sewer system, treatment plant and receiving water body. This integrated model is used to predict water flow and quality in the river. Additionally Doglioni *et al.* (2009) assessed the effect of new dwellings on the existing water facilities in an integrated framework made by a land use change model, a sewage system simulator, and a WWTP simulator. The three models are integrated into a Simulink model. Also Whitehead *et al.* (2009) applied the INtegrated CAthment (INCA) water quality to assess the likely impacts of climate change on water quality of six rivers across the UK.

RTC of the urban wastewater systems has received attention recently and meanwhile integrated modelling of the system has the advantage that information from all parts of the wastewater system can be used for control decisions and can lead to a significant improvement of the performance of the wastewater system. The application of the integrated modelling approach for RTC of the urban wastewater systems was reviewed by Schütze *et al.* (2004). In line with this Zacharof *et al.* (2004) applied the SYNOPSIS model for the integrated modelling of urban wastewater systems. It was aimed in this study to

develop a screening procedure to set up the RTC of an urban catchment without the necessity of execution a detailed modelling assessment procedure. This process was effectively applied to a range of real catchments and managed to identify sites with existing RTC as having high potential. Also Vanrolleghem *et al.* (2005) used a mathematical model for integrated modelling of the urban wastewater system. In this study an immission-based RTC scheme was applied to deal with the water quality legislations and it is used for a case study. Beck (2005) investigated the role of High-Performance Integrated Control (H-PIC) -a combination of RTC and IUWM-as an approach essential to managing water quality in developing watersheds. Advantages of integrated analysis of the urban wastewater systems have been addressed by Butler & Davies (2011). They demonstrated theoretically that a significant improvement in performance of the system can be achieved by the integrated RTC as it considers the interactions between different components of the system. In the context of an IUWS, Vojinovic (2011) investigated the impact of real-time pollution management for different case studies. The main tasks of this study were assessing the present functionality of the system, reviewing the alternative rehabilitation schemes and finally recommendations for upgrading the systems. In this study he focused on CSO to the river, groundwater infiltration, river back flows, sewer sediment, WWTP loads and impact on receiving water.

Some of the recent studies have linked the integrated modelling approaches in urban wastewater systems with the optimisation techniques, to improve the system performance aiming to meet to the water quality criteria. This was done in a study by Butler & Schütze (2005) to improve the river water quality in an urban wastewater system as a whole. In this study, a simulation package SYNOPSIS encompasses sub-models of the sewer system, treatment plant and river was developed and tested on a case study. Then the benefits of integrated modelling of the operational control of the urban wastewater systems were investigated. In their results they discussed that with integrated approaches, there is no longer necessary to use simplified criteria in modelling and it is feasible to operate complete urban wastewater systems to maximise river water quality directly. Also Polaskova *et al.* (2006) applied an integrated approach for optimising the operation of sewerage systems. The applied integrated modelling approach provided the potential of better utilising the storage capacity of the

sewer system to reduce the CSO. Muschalla (2008) developed a pollution-load and water-quality model to optimise the performance of the urban wastewater system in an integrated framework. In this study the integrated model was combined with a new multi-objective evolution strategy. The model developed was validated by analysing a real catchment area including sewer system, WWTP, water body and river. In a study by Fu *et al.* (2008a) an integrated approach was applied to simulate the urban wastewater systems. This integrated simulation model was combined with a multiple objective optimisation model to improve the water quality in the river. In other words, this integrated approach helped considering the water quality indicators as the operational control optimisation objectives directly, rather than by reference to surrogate criteria in the sewer system or treatment plant. The latter researchers (Fu, *et al.*, 2010) applied the integrated modelling perspective to investigate the optimal distribution and control of storage tanks with an objective to mitigate the impact of new residential development on receiving water quality. The optimal storage distribution resulted in this study shows the benefits of direct evaluation of receiving water quality impact in an integrated framework.

Another recent and important application of the integrated modelling approach has been used for the uncertainty/risk analysis in a few recent studies. This can enhance the reliability to get to more sustainable urban wastewater systems under the future changes. In line with this, Sarang *et al.* (2008) applied a risk-based approach to quantify and assess the degree of relative sustainability of water in Karoun River in Iran. For this purpose they developed a tool with an integrated approach consisting of two main parts: a water quality simulation model and an estimation of risk-based indicators model. Also Schellart *et al.* (2008) applied the deterministic Integrated Catchment Modelling (ICM) to determine the levels uncertainty analysis in the prediction of water quality failures in a case study in the UK.

For the purpose of integrated modelling explained above, having a good and efficient tools or methods are necessary to better simulate quality and quantity components of the systems. Schütze *et al.* (2002a) presented a list of existing softwares for modelling different components of the IUWS comprised sewer system, WWTP and river. Table 2.1 was provided in this study to summarise

the tools, methods and approaches applied for the IUWS modelling in the above mentioned studies.

With regard to the recent developments in software developing, (such as SIMBA) now there is less need to simplify the case studies in the simulation processes as done by Butler & Schütze (2005) which can bring uncertainties to the modelling. Due to the complexity of the IUWS modelling tools, methods or softwares which are users friendly are preferred. For instance using SIMBA tool which is a Simulink-based software has provided a visual opportunity for the engineers to simulate the IUWS components easier than the only mathematical-based model (e.g. Polaskova *et al.* (2006)).

Additionally with regard to the importance of the water quality management and its impact on the environment approaching to the sustainable systems and meeting the environmental criteria looks necessary. In line with this, Table 2.1 emphasises the importance of water quality management. As it can be observed Dissolved Oxygen (DO) and ammonia concentrations are the most important water quality indicators in all these studies.

Table 2.1 List of studies using the integrated modelling approach in urban wastewater

No.	Author (s)	Aim	Tool/method/Approach	Water quality parameters (Conc. ¹)	Case studies
1	Kallis & Butler (2001)	WFDL ²	-	-	-
2	Zacharof <i>et al.</i> (2004)	RTC ³ -WQ ⁴	Simulation package SYNOPSIS	DO & ammonia	(Schütze, 1998)
3	Schütze <i>et al.</i> (2004)	RTC-REW ⁵	-	COD, ammonia	Québec Urban Community
4	Vanrolleghem <i>et al.</i> (2005)	WFDL-WQ	Sewer system: Hydroworks (Wallingford Software, UK), WWTP: ASM2d model, River water quality: a mechanistic model developed	Un-ionised ammonia	Tielt town catchment in Belgium
5	Butler & Schütze (2005)	WQ-RTC	Simulation package SYNOPSIS	DO & ammonia	(Schütze, 1998)
6	Beck (2005)	WQ- REW-RTC	High-Performance Integrated Control (H-PIC) approach	DO & BOD	-
7	Sarang <i>et al.</i> (2008)	UA ⁶ -WQ	QUAL2E-U model	DO & BOD	Karoun River in Iran
8	Polaskova <i>et al.</i> (2006)	OPT ⁷ -RTC	A mathematical simulation model developed	BOD	The town of Třebíč
9	Wilby <i>et al.</i> (2006a)	IA ⁸ -WQ	Linking regional climate model: SDSM, water resources model: CATCHMOD and water quality model: (INCA)	Nitrate & AMM ⁹	River Kennet in UK
10	Muschalla (2008)	OPT-WQ	An integrated simulation model developed and linked to an optimisation algorithm	DO, BOD/COD & Nitrogen	River Bieber in Germany
11	Schellart <i>et al.</i> (2008)	UA-WQ	Integrated Catchment Modelling (ICM): MIKE NAM, Infoworks CS, MWH UK, STORMPAC	DO, BOD, un-ionised ammonia	A UK catchment
12	Fu <i>et al.</i> (2008a)	WQ	Linking SIMBA and evolutionary optimisation algorithm (NSGA-II)	DO & AMM	(Schütze, 1998)
13	Fu <i>et al.</i> (2009)	WQ	SIMBA (SWMM, ASM1)	DO & AMM	(Schütze, 1998)
14	Dogliani <i>et al.</i> (2009)	IA-WQ	land use change model: LUC, urban drainage model: SWMM, WWTP: ASM1	COD, BOD, TotN, TSS	A town in Scotland
15	Whitehead <i>et al.</i> (2009)	IA-WQ	INtegrated CAatchment (INCA) water quality model	Phosphorus & nitrate	Six catchments in the UK
16	Fu <i>et al.</i> (2010)	WQ	SIMBA (SWMM, ASM1)	DO & AMM	(Schütze, 1998)
17	Vojinovic & Mark (2011)	WQ	MOUSE, MIKE21, historical data	Coliform	Thailand
18	Vojinovic (2011)	IA	MOUSE and MIKE21	-	-

1. Conc.: Concentration;
2. WFDL: Deal with WFD legislations;
3. RTC: Real time control;

4. WQ: Water quality management/assessment;
5. REW: Review paper;
6. UA: Uncertainty/risk analysis;
7. OPT: Optimisation;
8. IA: Impact assessment (on water quality);
9. AMM: Ammonium.

2.3. Climate Change and Urbanisation Impacts on IUWS Performance

Assessment of the potential impact of climate change and/or anthropogenic activities on wastewater systems performance, in terms of water quality, has been an essential part of hydrological research over the last couple of decades. Below gives a summary of the recent and most relevant studies to this thesis.

Several explorations of the potential implications of climate change for the use and management of water quality have been done. For example Arnell (1998) applied feasible climate change scenarios for UK to observe the changes in river flows, groundwater recharge and river water quality. The results of these investigations showed an increased stress on the water resource in UK in the future. These stresses will have influence on the reliability of water supplies, navigation, aquatic ecosystems, recreation and power generation, and will have implications for water quality management.

To investigate the future potential impacts of climate change on river water quality, GIS-based softwares are very useful for the purpose of modelling. In line with this, Mimikou *et al.* (2001) applied two General Circulation Models (GCM)-based climate change scenarios (by the year 2050) to assess their impacts on surface runoff and water quality (including Biochemical Oxygen Demand (BOD), DO and AMM in the river). In this study, surface runoffs was quantified with the use of a physically-based rainfall runoff model, the climate change scenarios are on the GCM and water quality parameters are estimated by using an in-stream model (R-Qual).

A comprehensive study about climate change impacts and implications was done by joining the Intergovernmental Panel on Climate Change (IPCC), World Meteorological Organization (WMO) and the United Nations Environment Programme (UNEP). In these studies, they aimed to provide an authoritative international statement of scientific understanding of climate change. For this purpose the most inclusive sources are the IPCC's periodic reports about different aspects of climate change. These reports are the most up-to-date

reports available in academia, government and industry worldwide. The climate change in IPCC reports are considered to any change in climate over time, whether due to natural variability or as a result of human activity. A few of the most important reports are included in the next few paragraphs:

IPCC (2000) has published a special report on emission scenarios. In this report the long-term emission scenarios were developed which are used in the analysis of possible climate change, its impacts, and options to mitigate climate change. In a Technical Paper Report provided from this report, it was focused on evaluating the impacts of climate change on hydrological processes and regimes, and on freshwater resources – their availability, quality, uses and management.

Another comprehensive and useful report was provided by Hulme *et al.* (2002) from the Hadley Centre for Climate Change in the UK Climate Change. In this Report they presented a set of four scenarios of future climate change for the UK based on the current understanding of the science of climate change. These climate change scenarios are based exclusively on the experiments recently completed using the HadCM3, HadAM3H and HadRM3 climate models. In these scenarios three time horizons 2020, 2050 and 2080 are defined and future climate changes under these periods are presented in detail. In addition to these, this report summarises the changes that are already occurring in global and UK climate. In addition, it presents four alternative climate change scenarios for the UK, including information about changes in average climate and extreme sea levels around the coast. In this report the main uncertainty that has influence on our confidence in these descriptions, and illustrates the importance of some of them are discussed. One advantage of this report is that it directs users to further sources of information, both quantitative and qualitative, that will assist them in using the UKCIP02, and other, climate change scenarios when conducting scoping, impacts or adaptation studies in the UK.

In addition to the climate change factors, other indicators of future changes can be applied for the impact assessments on rivers' water quality. For example Drago & Brekke (2005) assessed the effects of two carbon dioxide increase scenarios and three associated climate change projections on the Lake Cachuma hydrology and water quality. The assessment indicates that under a

variety of climate change scenarios of a warming climate, the likelihood of taste and odour events during the dry season would increase and turbidity and apparent colour events would be more likely if precipitation rates increase.

Later on Whitehead *et al.* (2009) studied on modelling to assess the likely impacts of climate change on water quality of six rivers across the UK. Several climate change scenarios have been used to generate future precipitation, evaporation and temperature time series in whole catchments across the UK. The INtegrated CAatchment (INCA) water quality models are applied in this study to model the flow and water quality parameters. The models were run for four UKCIP02 climate change scenarios and for three periods (the 2010s, the 2020s and the 2050s).

A Synthesis Report was published by IPCC (2007) based on the assessment carried out by the three Working Groups (WGs) of the IPCC. This report provides an integrated view of climate change as the final part of the IPCC's Fourth Assessment Report (AR4). This report includes 6 sections explaining about; observed changes in climate and their effects on natural and human systems, regardless of their causes, assessing the causes of the observed changes, projections of future climate change and related impacts under different scenarios, adaptation and mitigation options over the next few decades and their interactions with sustainable development, assessing the relationship between adaptation and mitigation on a more conceptual basis and takes a longer-term perspective and finally the major robust findings and remaining key uncertainties in this assessment.

The Task Group on Data and Scenario Support for Impact and Climate Assessment (TGICA) was formed by IPCC, in 1997. The responsibility of this group is to provide regional climate change information with particular focus on capacity building for future IPCC assessments. This group aims to offer guidance on the interpretation and application of scenario data in impact and adaptation assessment. Therefore IPCC-TGICA (2007) provided a completely revised version of Special Reports on Emission Scenarios (IPCC, Emission Scenarios: Special Report of Working Group III to the IPCC, (2000)) in parallel with the generic guidelines, concerning: Climate scenarios developed from regional climate model experiments; climate scenarios developed using

statistical downscaling techniques; global and regional sea level scenarios; socio-economic scenarios; scenarios of atmospheric composition.

The impacts of climate change especially precipitation changes as one of the important climate change indicators on the quantity of water resources were investigated in several studies. For example the impacts of climate change on the design and performance of sewer storage tank for a case study in London was investigated by Butler *et al.* (2007). The climate change parameter considered is a long-term synthetic rainfall time-series under the IPCC medium-high emission scenario. In this study a method to estimate the required future storage volume for any given return period has been developed and described. With a number of floods in urban areas happening by heavy rainfalls around the world in recent years.

In the PhD thesis of Olofsson (2007) these intense rains' expected damages to people and real estate in the future was investigated. In this thesis it was investigated how the change in precipitation and temperature will influence the urban drainage systems and how measures can be taken to prevent or reduce the consequences of floods. Also this thesis presents methods and results on how to simulate what effect the changed precipitation will have on urban drainage.

Also Nie *et al.* (2009) investigated the possible consequences in the sewer system in Veumdalen catchment, in the present, predicted and artificial climate scenarios. In this study surface flooding, surcharging sewers, basement flooding and CSO are considered as performance indicators of the system under climate change. Additionally a Technical Report was provided by Bates *et al.* (2008), focused on two main issues as outlined in IPCC-XXI/Doc.9 (2003) to evaluate the impacts of climate change on hydrological processes and regimes, and on freshwater resources, their availability, quality, uses and management. This report considers the current and projected regional key vulnerabilities and prospects for adaptation. Secondly it is addressed primarily to policymakers engaged in all areas relevant to freshwater resource management and climate change.

The anthropogenic activities, urbanisation and future developments have the potential to affect the quality of water. These impacts are unavoidable but

controllable. As this study will consider the future impacts of urbanisation changes on the quality of water, therefore studies relevant to this purpose are reviewed here.

Following the aforementioned anthropogenic activities Beck (2005) investigated the vulnerabilities impacted from growing cities on the ecological health and re-invigoration of their corresponding watersheds. In this study the implications of technocracy-based technologies to the democracy-based (stakeholder participation) ones were investigated. For this purpose, a combination of RTC and Integrated Urban Water Management (IUWM) approaches were applied to manage water quality in developing watersheds.

Urban growth impact on streamflow was investigated in a study by Choi & Deal (2008). In this study they connected a cellular, dynamic, spatial urban growth model and a semi-distributed continuous hydrology model to quantitatively predict streamflow in response to possible future urban growth at a basin scale. The results indicate that dynamic simulation modelling by connecting a distributed land use change model and a semi-distributed hydrological model can be a good decision support tool demanding a reasonable amount of effort and being capable of long-term scenario-based assessments.

GIS-based software in addition to climate change modelling is used for the purpose of urbanisation modelling as well. Due to the high potential and good accuracy of these models, the results obtained can better indicate impacts. In line with this, He *et al.* (2008) studied the response of surface water quality to urbanisation in Xi'an, China and has used GIS for evaluating the impacts of urbanisation on land use and surface water quality from 1996 to 2003. In this study both statistical methods and GIS techniques were applied. Their findings showed a strong relationship between land use and surface water quality.

Also Doglioni *et al.* (2009) investigated the annual expansion of an urban area according to planners' guidelines and the response of the drainage system to the expansion in an integrated framework of urban wastewater system. The proposed framework is tested on a simple case study of a small town located in south west of Scotland.

The impact of new developments on river water quality was quantified by Fu *et al.* (2009) in an integrated urban wastewater system. A semi-hypothetical urban

catchment is considered in this study and the water quality is investigated by 'locating' a new development in the river catchment. The system is analysed under these new developments at various reaches of the river in which the CSO discharges and treatment plant effluent are the sources of pollution releases to the river. The results of this study can help decision makers, town planners and water specialists to mitigate the negative impacts of such developments on water systems.

Urban Creep (as one of the features of urbanisation) has been known as a growing problem for sewerage which affects CSO spills, pumping costs, treatment costs, flooding and water quality. There are many drivers for urban creep and there is a complex mixture of different variables acting as drivers. UKWIR (2009) has investigated the use of remote sensing technology to detect urban creep and has allowed large samples to be studied in various locations across England and Wales which has enabled large and statistically valid sample sets to be extracted and analysed.

Jacobson (2011) reviewed the methods that have quantified and modelled the impacts of urban imperviousness on hydrological systems. In this study the nature of reported impacts of urbanisation on hydrological systems over four decades are tested. These reviews include the effects of changes in imperviousness within catchments, and some inconsistencies in studies of the impacts of urbanisation. Also in this study the ways in which scientists and hydrological and environmental engineers model and quantify water flows in urban areas, the nature of hydrological models and methods for their calibration are examined. Furthermore additional factors which influence the impact of impervious surfaces and some uncertainties that exist in current knowledge were tested.

The combined impacts of future climate change and anthropogenic activities have significant impact on water resources, especially the quality of water. In the past these combined impacts have been less focused but recently more efforts have been to address this issue. The aforementioned combined approach considers the interaction between the systems and has the potential to give more reliable and precise results for the purpose of water quality management. In line with this, the combined impacts of climate change and landuse change on river water quality (nitrate-nitrogen) was investigated in a

study in Scotland by Ferrier *et al.* (1995). In this study, the river water quality model QUASAR (Quality Simulation Along River) has been applied to simulate the river. The climate changes were considered as a number of scenarios and the landuse changes were assumed as agricultural patterns. Therefore the simulations were performed under these climate change parameters.

Additionally the quality of water in Schuylkill River was assessed and investigated by Interlandia & Crockett (2003). In this study climate, flow rate and land use were considered as the known drivers of water quality. For this purpose the relative influences of precipitation, river discharge and land-use change in this watershed were addressed. For the climate driver, century scale trends and seasonal patterns in regional climate were considered. Moreover the recent trends in water chemistry and land-use change in the region are depicted.

Later on Wilby *et al.* (2006b) studied the impacts of climate change and land use change on the River Kennet to investigate aspects of climate change uncertainty, water resources and water quality dynamics in upper and lower reaches of the drainage network. This was performed by linking established models of regional climate (SDSM), water resources (CATCHMOD) and water quality (INCA) within a single framework.

Also the potential impacts of climate change and urbanisation on waste and stormwater flows in the combined sewer of central Helsingborg, South Sweden was investigated by Semadeni-Davies *et al.* (2008). Two climate change scenarios and three urbanisation storylines were considered to model the future changes. For this purpose, the DHI MOUSE tool was used for simulations under present conditions. Climate change was simulated by altering rainfall derived from a regional climate model. Urbanisation was simulated by changing model parameters to imitate the demographic changes. Their findings showed that city growth and projected increases in precipitation, both together and alone, bring about problems to the current drainage system.

Later on Tu (2009) investigated the combined impact of climate and land use changes on streamflow and water quality. These analyses were performed by using a GIS-based watershed simulation model, AVGWLF, to simulate the

future changes in streamflow and nitrogen load under different climate change and land use change scenarios in watersheds of eastern Massachusetts.

The combined approach was followed in a study by Cox & Whitehead *et al.* (2009). They investigated the likely impacts of future climate changes and urbanisation on DO dynamics along the Thames river system and the probability distributions associated with future variability. Consequently the water quality will be highly dependent on the activities in the future. For this purpose, the Q² model was used to assess the aforementioned impacts on DO. The projected emissions scenarios for the 2080s (Hulme, *et al.*, 2002) represent the future climate change projections in this study and HadCM3 developed by the UK Met Office Hadley Centre has been used to simulate changes in UK climate. Also as the Thames catchment is densely populated, therefore urbanisation relies on population growth in the future so therefore the impacts of the future population on potable water supply and disposal route for treated wastewater were assessed in this study.

Also recently Storch & Downes (2011) presented an approach to quantifying current and future city-wide flood risks to Ho Chi Minh City. In this study, urban planning scenarios were considered linking urban development and climate change as the main driving forces of future risk. The results in this research highlights that the spatiotemporal processes of urban development, together with climate change, are the driving forces for climate-related impacts. The findings of this study can aid local decision making in an effort to better understand the nature of future climate change risks to the city and to identify the main driver of urban exposure.

At the same time with the aforementioned study Wilson & Weng (2011) studied the future impacts of urban land use and climate changes on surface water quality within Des Plaines River watershed, Illinois, between 2010 and 2030. Land Change Modeller (LCM) was used to characterize three future land use/planning scenarios. Each scenario represents low density residential growth, normal urban growth, and commercial growth, respectively. Future climate patterns examined include the IPCC Special Report on Emission Scenario (SRES) B1 and A1B groups. The Soil and Water Assessment Tool (SWAT) was employed to estimate total suspended solids and phosphorus concentration generated at a 10 year interval. The combined land use and

climate change analysis revealed land use development schemes that can be adopted to mitigate potential future water quality deficiency. This research provides important insights into possible adverse consequences on surface water quality and resources under certain climate change and land use scenarios.

The combined impacts of climate change and urbanisation also can affect economic and social development parameters. In line with this Gu *et al.* (2011) explored these impacts for the Yangtze River Delta (YRD). This paper explores such interrelationship from two perspectives. On one hand, they used historic data, by summarising the urbanisation process in the YRD and with climate change. On the other hand, they considered the urbanisation process without future climate change. Potential effects include large flooded land area, flood disasters, production and energy inefficiency, and other environmental threats. Their results showed that it is imperative to adopt policies and programs to mitigate and adapt to climate change in the fast urbanisation process.

Also Tong *et al.* (2012) described a spatial analytical approach integrating mathematical modelling and geographical information sciences to quantitatively examine the relative importance of the separate and combined hydrologic and water quality impacts of climate and land use changes. They used the Little Miami River (LMR) watershed as a case study. In this study five hypothetical climate change scenarios were used to cover the possible ranges of variability in the year 2050. An enhanced population-coupled Markov-Cellular Automata (CA-Markov) land use model was developed to predict the 2050 land use pattern. The described approach is effective in simulating the hydrologic and water quality effects of climate and land use changes in a basin scale. Their results are relevant to planners; they can be useful in formulating realistic watershed management policies and mitigation measures.

Table 2.2 shows a summary of studies investigating the impacts of climate change and/or urbanisation on the quality of water in the IUWS. As can be observed, nearly all of the studies have applied a scenario-based approach on the basis of the IPCC future climate change projections. The IPCC future projections can represent a comprehensive detail of the future climate changes and therefore can be applied for the purpose of the climate change modelling. This study has used this approach by applying the future projections provided

for the UK by Hulme *et al.* (2002). For the purpose of climate change modelling, softwares or tools developed by the UK Met Office Hadley Centre have been applied in some of the studies presented in Table 2.2 and for different case studies around the world (e.g. HadCM2 and UKCIP09). Additionally, DHI GIS-based software such as MOUSE is used to investigate the impacts of climate change on the quality of water. Meanwhile the IPCC tools developed such as RCM, CCM3 and CGCM3.1 and several others have been used in different studies as well. It should be noted here that GIS-based tools for climate change modelling pre-processing and post-processing (e.g. downscaling) need to be used to obtain accurate results and this requires accurate and sufficient Digital Terrain Model (DTM) maps. Therefore sometimes it is difficult to provide such detail information for the study and hence selecting these tools and software for this purpose is dependent on the case study in hand.

Also it can be observed in Table 2.2 that fewer studies have focussed on future urbanisation modelling and its impacts on water quality. In the few studies investigating the impacts of future urbanisation on the water quality, a scenario-based approach has been applied. Some of these studies have used the storylines developed by the IPCC for the future urbanisation such as Semadeni-Davies *et al.* (2008).

A key observation from this table is that the combined impacts of climate change and urbanisation have not been studied as comprehensively but recent efforts to develop tools/softwares to solve this problem could provide this possibility to some extent. For example in a new developed integrated model like SIMBA, has provided a user friendly application. This tool has been used by Fu *et al.* ((2008b), (2009) and (2010)) and is efficient for the purpose of integrated modelling.

As the ultimate aim in this study is to demonstrate how urban wastewater system can maintain the quality of water in the river, having an efficient tool for this purpose is important. Different software has been used in the studies in Table 2.2 to model the river water quality under the future changes. Selecting a proper model for this purpose depends on the requirements and the information exists for modelling. For instance the river water quality model QUASAR used by Ferrier *et al.* (1995) is a water quality and flow model for river networks. It is designed to be used by river regulatory authorities and water/sewerage utility

companies to help manage river water quality while the SWAT water quality model is an integrated modelling framework constructed for the Soil and Water Assessment applied by Wilson & Weng (2011) which for the purpose of land use changes it was necessary to consider soil as well.

Table 2.2 Summary of the studies focused on the impacts of climate change and/or urbanisation on the quality of water in the IUWS

No.	Author (s)	Aim	Water quality parameter (Conc. ¹)	CC ⁷	Urb ⁸	CCU ⁹	Model type/Approach	Case study
1	Ferrier <i>et al.</i> (1995)	WQ ³	Nitrate	IPCC scenarios	Agricultural patterns	Yes	River quality model : QUASAR	River Don in Scotland
2	Arnell (1998)	WQ	DO & nitrate	IPCC scenarios	NO	NO	(Arnell & Reynard, 1996) Water quality model: R-Qual, Climate change models: UKHI and HadCM2	UK catchments
3	Mimikou <i>et al.</i> (2001)	IA ⁵	BOD, DO & AMM ⁶	Climatic Research Unit scenarios	NO	NO		Pinios river in Greece
4	Hulme <i>et al.</i> (2002)	CC in UK	-	-	NO	NO	UKCIP02	UK
5	Interlandia & Crockett (2003)	WQ	Nitrate, Chlorid, ammonia	Precipitation data from National Climatic Data Centre	Agriculture , forest data from National Resources Conservation Service	YES	Models developed for analysis	Schuylkill River in US
6	Beck (2005)	RTC ² -WQ	DO & BOD	NO	Urban landscape	NO	High-Performance Integrated Control (H-PIC) approach CC models: HadCM2, PCM, CCM3;	Hypothetical
7	Drago & Brekke (2005)	IA-WQ	DO, TDS, turbidity	IPCC scenarios	NO	NO	Discriminant analysis Model for water quality RCM ¹⁰ : SDSM, water resources: CATCHMOD, water quality model: INCA	Lake Cachuma in US
8	Wilby <i>et al.</i> (2006b)	IA	Nitrogen	IPCC scenarios	NO	NO		River Kennet in UK
9	Butler <i>et al.</i> (2007)	IA on sewage system performance	-	IPCC scenarios	NO	NO	Hadley Centre's Europe RCM	Area of North London
10	Olofsson (2007)	IA on urban drainage	-	IPCC scenarios	NO	NO	RCM: RCA3	A city in the Sweden
11	Choi & Deal (2008)	IA on surface flow	-	NO	land use scenarios	NO	Land use scenarios generator: LEAMluc, Hydrologic Simulation Program: HSPF embedded in BASINS	Kishwaukee River in US

No.	Author (s)	Aim	Water quality parameter	CC	Urb	CCU	Model type/Approach	Case study
12	Semadeni-Davies <i>et al.</i> (2008)	IA on Combined Sewer systems	-	IPCC scenarios	IPCC urbanisation on story lines	YES	DHI MOUSE for sewer system	Helsingborg in Sweden
13	He <i>et al.</i> (2008)	IA-WQ	BOD, COD, Phosphorus	NO	Mathematical model developed	NO	Meta model developed using ANN and water quality samples collected	Xi'an, China
14	Tu (2009)	IA-WQ	Nitrogen load	Scenarios developed	Scenarios developed	YES	Watershed simulation model: AVGWLF; CC model: CGCM3.1	Metropolitan Boston
15	Nie <i>et al.</i> (2009)	IA on urban drainage system	-	Scenarios developed	NO	NO	DHI- MOUSE program	Veumdalen catchment in Norway
16	Cox & Whitehead (2009)	IA-WQ	DO	IPCC scenarios	NO	NO	River quality simulation model: Q ² Integrated Catchment (INCA)	River Thames in London
17	Whitehead <i>et al.</i> (2009)	IA-WQ	Nitrate, ammonia & phosphorus	IPCC scenarios	NO	NO	water quality model Land use change model: LUC, urban drainage model: SWMM, WWTP: ASM1	Six UK rivers
18	Dogliani <i>et al.</i> (2009)	IA-WQ	COD, BOD, TotN, TSS	NO	YES	NO	water quality model: SWMM, WWTP: ASM1	A town in Scotland
19	Fu <i>et al.</i> (2009)	IA	DO & AMM	NO	Scenarios developed	NO	SIMBA	(Schütze, 1998)
20	Storch & Downes (2011)	IA	-	Scenarios developed	Scenarios developed	YES	DTM modelling	Ho Chi Minh City in Vietnam
21	Gu <i>et al.</i> (2011)	IA	-	Carbon emission, temperature & sea level rise data	Population, area, GDP data collected	YES	-	Yangtze River in China
22	Jacobson (2011)	IA- REW ⁴	-	-	Imperviousness scenarios developed	NO	Vegetation-Impervious surface-Soil (V-I-S) model	Hypothetical
23	Wilson & Weng (2011)	IA-WQ	TSS & Total phosphorus	IPCC scenarios	IPCC land use scenarios	YES	Land Change Modeler (LCM), Water quality model: SWAT model	Des Plaines River in US
24	Tong <i>et al.</i> (2012)	IA-WQ	Phosphorus & nitrogen	Hypothetical CC scenarios developed	Land use meta model developed by Cellular Automata	YES	Water quality model: Hydrologic Simulation Program e-Fortran (HSPF)	Miami River watershed

1. Conc.: Concentration;
2. RTC: Real time control;
3. WQ: Water quality management/assessment;
4. REW: Review paper;
5. IA: Impact assessment (on water quality);
6. AMM: Ammonium;
7. CC: Climate change;
8. Urb: Urbanisation;
9. CCU: Combined climate change and urbanisation;
10. RCM: Regional climate model.

2.4. Sensitivity, Uncertainty and Risk Analysis

Projections of future climate change and urbanisation are plagued with uncertainties which bring risks to decisions made and also cause difficulties for planners on adaptation measures. UNESCO (2011) reported that considering future global changes (due to climate changes, anthropogenic activities) and identifying risks and uncertainties was key to urban water and wastewater management.

With regard to the impact of water quality on the health of aquatic life, recognition of the sources of uncertainty in water quality can lead to more reliable assessments of the risk in water quality. Additionally it can help decision makers to come up with more consistent decisions. There is a variety of literature promoting understanding and application of uncertainty analysis and/or risk assessments/analyses in water quality modelling. In the following a number of most relevant (to this thesis) and recent studies are presented.

For the purpose of risk assessment a novel approach was presented by Mc Avoy *et al.* (2003) to assess the risk of untreated wastewater produced by the consumers was and tested on the Balatuin River in Philippines. The QUAL2E model is used for water quality simulation to predict the impact caused by pollutants. This approach considered an *impact zone concept* whereby the receiving water can be thought of as a natural wastewater treatment system. After the river recovery via self-purification, the ecosystem is then assessed by traditional risk assessment methods.

Later on aiming toward a sustainable onsite wastewater treatment (OWTS) with minimal impacts on the environment and public health, Carroll *et al.* (2006) applied an integrated risk-based approach for assessing the inherent hazards in order to manage and mitigate the environmental and public health risks. In developing a consistent integrated risk framework for OWTS, several key factors must be known. These include the inclusion of relevant stakeholders throughout framework development, the integration of scientific knowledge, data and analysis with risk assessment and management ideals, and identification of the appropriate performance goals for successful management and mitigation of associated risks. These issues were addressed in the development of the risk framework to provide a generic approach to assessing risk from OWTS. The

utilisation of the developed risk framework was used for a case study in Australia.

Additionally, a method to assess the risk of water degradation in harbour domains by using hydrodynamic models was developed by Grifoll *et al.* (2010). The risk of water degradation due to a pollution event is determined by a normalized Index of Risk (ranging from 0 to 1). To obtain this index a branch-decision scheme of decision-making theories is applied. This method evaluates the cost of each decision as a function of the vulnerability, proximity and toxicity of the potential contaminant. The implementation of urban development plans causes land use change, which can have significant environmental impacts. In line with this, environmental distresses should be considered in the planning process. However, uncertainties existing in urban development plans obstruct the application of strategic environmental assessment, which is applied to evaluate the environmental impacts of policies, plans and programs.

Flores-Alsina *et al.* (2010) studied the benefits of complementing environmental assessment with economic, technical and legal criteria. In this study for the purpose of the assessment of WWTP economic (e.g. operation costs), technical (e.g. risk of suffering microbiology-related TSS separation problems), legal (e.g. achievement with the effluent standards in terms of the different pollution loads) were considered. In this study a preliminary version of the Benchmark Simulation Model no. 2 (BSM2) was applied as a case study.

An aquatic risk assessment approach was implemented by Vryzas *et al.* (2011) based on the Risk Quotient regarding three trophic levels, algae, aquatic invertebrates and fish. This study combines monitoring and ecotoxicological data aiming to assess pesticide loading in the drainage canals of two transboundary rivers (near the Greek/ Bulgarian/Turkish borders). The aquatic risk assessment revealed non-acceptable risk for a number of compounds and if extreme concentrations are taken into account more compounds were considered as likely to pose a threat to aquatic organisms.

A new risk assessment approach was applied in a study by Gottardo *et al.* (2011) named Integrated Risk Assessment (IRA) methodology based on the Weight of Evidence approach. This method analyses and combines a set of environmental indicators grouped into five Lines of Evidence (LoE), i.e. Biology,

Chemistry, Ecotoxicology, Physico-chemistry and Hydromorphology. The whole IRA methodology has been implemented as a specific module into a freeware GIS-based Decision Support System, named MODELKEY DSS. This study focuses on the evaluation of the four supporting LoE and includes a procedure for a comparison of each indicator with proper thresholds and a subsequent integration process to combine the obtained output with the LoE Biology results in order to provide a single score expressing the Ecological Status classification.

Quantification of the uncertainty is imperative. However, despite the importance of uncertainty quantification, only a few studies have been carried out in the wastewater treatment field, and those studies only included a few of the sources of model uncertainty.

Therefore the problem of uncertainty has been addressed by Al-Redhwan *et al.* (2005) to optimise water networks in process industries. The uncertainties considered in this study are derived from actual operational practice of major water-using units in a typical oil refinery. A sensitivity analysis was performed and the results revealed that considering uncertainty in operating conditions has considerable changes in the connectivity of the units involved in wastewater reuse. The proposed stochastic approach in the optimisation model makes a flexible and resilient wastewater network.

Later on in a case study the levels of uncertainty in the prediction of the number of failures of water quality standards was quantified by Schellart *et al.* (2008) by applying deterministic ICM. These uncertainties were associated with the model input and model parameters in models used in an ICM study. The uncertainty analysis was carried out by Monte Carlo (MC) simulations over a response database. This method determined the range in the number of predicted failures caused by uncertainties in the numerical tools currently used in ICM studies in the UK.

Additionally an uncertainty analysis of WWTP models was studied by Sin *et al.* (2009). In this study they defined three scenarios from engineering practice to frame the uncertainties and investigated how it affects the uncertainty analysis results. For this purpose, the MC procedure was used for uncertainty estimation and the input uncertainty is quantified through expert elicitation and the Latin

Hypercube method is used for sampling. The results show that, the uncertainty analysis method has significant impact on the estimated uncertainty of design performance criteria.

In line with the uncertainty assessment approach, Mannina *et al.* (2011) presented an uncertainty assessment of a mathematical model simulating biological nitrogen and phosphorus removal. The model was based on activated-sludge models 1 (ASM1) and 2 (ASM2). The uncertainty assessment was steered according to the Generalised Likelihood Uncertainty Estimation (GLUE) methodology that has been scarcely applied in the wastewater field as it requires a large number of MC simulations. Using this approach, model reliability was evaluated based on its capacity to globally limit the uncertainty. The method was applied to a large full-scale WWTP for which quantity and quality data was gathered. The analysis enabled useful insights to be gained for WWTP modelling identifying the crucial aspects where higher uncertainty rely and where therefore, more efforts should be provided in terms of both data gathering and modelling practices.

Uncertainty analysis is also important in the process of water quality management decision making. Flores-Alsina *et al.* (2008) used a simplified version of the IWA BSM no. 2 as a case study to show the variations in the decision making when the uncertainty in ASM parameters is either included or not during the evaluation of WWTP control strategies. The model performance firstly is evaluated under six WWTP control strategies using multi-criteria decision analysis with setting the ASM parameters at their default value. The inputs uncertainty is characterised by probability distribution functions based on the available process knowledge. Then, MC simulations are run to propagate input through the model and affect the different outcomes.

Recognising and assessing the uncertainties of future climate change projections can be the prelude of the future adaptation strategies required. In line with this an assessment framework for identification of adaptation strategies that are robust (i.e. insensitive) to climate change uncertainties was developed by Dessai & Hulme (2007) and was tested for a case study in the East of England. In this study in order to determine whether or not a decision to adapt to climate change, is sensitive to uncertainty in those elements, a local sensitivity analysis (a 'one-at-a-time' experiment) of the various elements of the

modelling framework (e.g., emissions of greenhouse gases, climate sensitivity and global climate models line HadCM3) was done. This study propounds a question that what levels of certainty in the water systems are required in the future.

Uncertainty analysis under the future climate changes can be linked to a risk assessment. Therefore Wilby *et al.* (2006b) assessed the potential risks of climate change to key phases of the River Basin Management Process that underpin the WFD (such as characterisation of river basins and their water bodies, risk assessments to identify pressures and impacts, programs of measures (POMs) options assessment, monitoring and modelling, policy and management activities) in the UK. The risks are identified with a view to informing policy opportunities, objective setting, adaptation strategies and the research agenda.

Uncertainties associated with climate-induced risks affect the quality of water in the rivers and also surface flows. In line with this, uncertainties in GCMs, in downscaling techniques and in hydrological modelling are three major sources of uncertainty surrounding climate change impact on river flows and were investigated by Prudhomme & Davies (2009). In this study, four British catchments' flow series simulated by a lumped conceptual rainfall–runoff model with observed and GCM-derived rainfall series representative of the baseline time horizon (1961–1990). Three GCMs (HadCM3, CCGCM2, and CSIRO-mk2) and two downscaling techniques (SDSM and HadRM3) were considered. Also variations in mean monthly flows due to hydrological model uncertainty (resulted from different model structures or model parameters) were considered.

To obtain a better understanding of the current status and climate-induced risks concerning surface water quality in East Asia, seasonal and spatial variations in surface water quality were compared among 11 watersheds in eight countries during typical dry and wet periods from 2006 to 2008 by Park *et al.* (2011). The results suggest that rainfall variability is crucial in understanding seasonality and climate-induced risks concerning surface water quality in East Asia.

Taking an economical point of view, recognizing the sources of uncertainties that exist might help water policy makers and planners to reduce costs. This

approach was applied in a study by Brouwer & De Blois (2008). They reviewed the most important sources of uncertainty when analysing the least cost way to reduce and eliminate bacteriological bathing water contamination. They presented the cost-effectiveness of water quality policy measures is surrounded by environmental, economic and political uncertainty. In this study these types of uncertainties were identified, quantified and analysed with the help of a new Excel-based risk model using MC simulation. They showed that the interaction between environmental and economic uncertainty is not straightforward and cannot simply be added or multiplied. The novelty of their study is that they investigate the combined effect of uncertainty in both the cost and effect assessment in a probabilistic way as a logical extension of traditional approaches to uncertainty analysis like sensitivity and scenario analysis used in most of the international literature so far.

In addition to economical uncertainties, Zhou *et al.* (2010) developed an integrated assessment method based on accounting uncertainty of environmental impacts. The proposed method consists of four main steps: (1) designing scenarios of economic scale and industrial structure; (2) sampling for possible land use layouts; (3) evaluating each sample's environmental impact; and (4) identifying environmentally sensitive industries. For this purpose, uncertainties of environmental impacts can be accounted for. Then overall environmental risk and pressure and potential extreme environmental impact of urban development plans can be analysed, and environmentally sensitive factors can be identified, particularly under considerations of uncertainties. It can help decision-makers enhance environmental consideration and take measures in the early stage of decision making.

Sensitivity analysis methods are useful as they can prioritize sources of uncertainty and quantify their impact on performance criteria. Sampling is an initial step in any uncertainty and sensitivity analysis techniques.

Saltelli *et al.* (2000) divided the sampling-based procedures into three groups: random sampling, importance sampling and Latin Hypercube Sampling (LHS). In line with the evaluation of these techniques' performance, Helton & Davis (2002) used a sequence of linear, monotonic, and non-monotonic test problems to illustrate sampling-based uncertainty and sensitivity analysis procedures. They compared the uncertainty results obtained with replicated random and

Latin hypercube samples, with the Latin hypercube samples tending to produce more stable results than the random samples. Their findings showed that a concern often expressed about sampling-based uncertainty and sensitivity analyses is that the number of required model evaluations will make the cost of the analysis prohibitive. In another study Helton & Davis (2003) summarised different techniques for uncertainty and sensitivity analysis and compared the performance of the MC and LHS methods together. Their investigations showed that no approach to the propagation and analysis of uncertainty can be optimum for all needs and depends on the particular problem.

Application of the sensitivity analysis in an IUWS management was investigated by Fu *et al.* (2009). They applied the regional sensitivity analysis (RSA) method to recognise the most effective new developments' parameters with the greatest impact on water quality. River water quality was used as feedback to constrain the scale of the new development within different thresholds in compliance with water quality standards. The results of these analyses can help the town planners and water engineers to manage the impact of such developments given the specific context.

Later on the effectiveness of global sensitivity analysis in WWTP design was demonstrated by Sin *et al.* (2011). In this study, the aim of global sensitivity analysis is to prioritize sources of uncertainty and quantify their impact on performance criteria. The study, which uses BSM no. 1 plant design, complements a previous paper on input uncertainty characterisation and propagation (Sin, *et al.*, 2009). Global sensitivity analysis was performed by linear regression on MC simulation model output. Overall, the Global Sensitivity Analysis (GSA) proved a powerful tool for explaining and quantifying uncertainties as well as providing insight into devising useful ways for reducing uncertainties in the plant performance. This information can help engineers design robust WWTP.

The evaluation of uncertainty in water quality modelling practice can be extended to risk management applications. For the purpose of risk management different approaches and tools can be applied. McIntyre *et al.* (2003a) applied WaterRAT tool for risk-based modelling of water quality as a potentially valuable component of a broader risk assessment methodology. The framework was outlined in five steps including identification of the factors affecting risk,

evaluation of risk associated with alternative pollution control strategies, consideration of alternative modelling criteria, consideration of different models for forecasting water quality response to pollution interventions and establishing priorities for collecting more data with which to improve model identification.

Relative sustainability of water quality systems including reliability, resilience, and vulnerability was quantified and assessed by Sarang *et al.* (2008) using a risk-based model tool. For this purpose the First Order Reliability Method (FORM) and MC simulation, were used. They concluded that the risk-based approach is an efficient tool for estimating the relative sustainability.

Additionally Sadiq *et al.* (2008) proposed an aggregative risk analysis approach using hierarchical structure to describe all possible mechanisms of contamination. Two types of uncertainties are considered in the proposed analysis. The first is related to the likelihood of risk events, and the second is related to non-linear dependencies among risk events. Each risk event (input factor) is defined using a fuzzy probability (likelihood) to deal with its inherent uncertainty. The proposed approach was applied for two well-known water quality failures in Canada, namely, Walkerton (ON) and North Battleford (SK).

In line with the risk analysis quantification, Chiou (2008) implemented a quantitative risk analysis to assess the health effects related to reclaimed water quality and to calculate the loading capacity of reclaimed wastewater in terms of the heavy metal accumulation. This study considered health risk, soil contamination and the influence of the reclaimed water on crop growth. Risk analysis was performed for compounds whose reference doses and/or unit risk values are available in the Integrated Risk Information System (IRIS) database maintained by the U.S. EPA.

Many factors such as operational, environmental conditions, factors in and around the systems affect the water quality in a system. Meanwhile quantification of water quality failure risk is very challenging because of the lack of reliable data in addition to the information gaps. Risk analysis in water quality management suffers from lack of information or imprecise data. Considering this, a fuzzy logic approach can be a good choice for the purpose of risk-based problem-solving. This approach was applied by Subbarao-Vemula *et al.* (2004) in a fuzzy waste load allocation model (FWLAM) for the evaluation of risk in a

river water quality management in southern India problem. In this study sensitivity analysis and first-order reliability analysis are applied to identify key random variables which influence the water quality simulation model output, and key checkpoints where the model output is more likely to be affected. Also the event of low water quality at a checkpoint in a river system is considered as a fuzzy event, with proper membership functions defined for the fuzzy risk of low water quality. With the help of fuzzy membership functions and frequency distributions, fuzzy risk values are computed at the key checkpoints.

Additionally the fuzzy approach was applied by Ghosh & Mujumdar (2006) as a fuzzy risk-based approach in a river water quality management problem. In this study sensitivity analysis, First Order Reliability Analysis (FORA) and MC simulations are performed to evaluate the fuzzy risk of low water quality. Results of the model developed are compared with the results of a deterministic FWLAM to show the effectiveness of the stochastic approach in water quality management problems.

For the purpose of risk and uncertainty analysis in the context of water quality assessments, a number of tools were developed. The risk-based modelling tool, WaterRAT, was developed by McIntyre & Zeng (2002) and applied to evaluate the uncertainty in water quality modelling practice for the risk management applications. The WaterRAT interface is a series of dialogue boxes and spreadsheets. It contains a library of water quality simulation models.

Additionally McIntyre & Wheeler (2004) developed a water quality Risk Analysis Tool (WaterRAT) for supporting decision-making in surface water quality management. The idea behind the software developed is that uncertainty in water quality model predictions is inevitably high due to model equation error, parameter error, and limited definition of boundary conditions and management objectives. Using sensitivity and uncertainty analyses based on MC simulation and first order methods, WaterRAT allows the modeller to identify the significant uncertainties, and evaluate the degree to which they control decision-making risk. WaterRAT has a library of river and lake water quality models of varying complexity and these can be applied at a wide range of temporal and spatial scales, allowing the model design to be responsive to both the modelling task and the data constraints.

Later on Sarang *et al.* (2008) developed a risk-based practical tool to assess the degree of relative sustainability of water quality systems. This tool includes a water quality simulation subroutine and an estimation of risk-based indicators subroutine.

At the same time Benedetti (2008) presented a set of tools developed to support an innovative methodology to design and upgrade wastewater treatment systems in a probabilistic way. This methodology includes the following four steps: data reconstruction, modelling and simulation, uncertainty analysis with MC simulations of the system and evaluation of alternatives. This study illustrates the advantages of these tools to make the innovative methodology of practical interest. It was concluded in this study that the design practice should move from conventional procedures, suited for the relatively fixed context of emission limits, to more advanced and cost-effective procedures appropriate to cope with the flexibility and complexity introduced by integrated water management approaches.

Table 2.3 shows a summary of the studies focused on risk analysis/uncertainty analysis/sensitivity analysis in water quality management. As can be observed, MC simulation is the dominant method used for risk/uncertainty/sensitivity analysis. It performs well in all the aforementioned analyses but this method is time consuming and is unsuitable for example in RTC of water systems. As can also be observed, the MC method is used and linked with other tools for the purpose of simulation and analysis. Meanwhile spread sheet-based tools (e.g. WaterRAT interface) are used for the purpose of simulations and risk analyses and are efficient and quick enough to cope with the time consuming MC if used (McIntyre & Wheater, 2004). What is notable in Table 2.3 is the frequent application of the scenarios-based approach for the purpose of risk analysis. As scenarios have the potential to indicate the projection of future changes and their likely impacts on the water systems, they are applied for the purpose of risk/uncertainty analysis by many researchers. Also RSA as a method for GSA is used in a few studies for sensitivity analysis. This can indicate the importance of considering the existing the interaction among the components in the integrated modelling approaches of urban wastewater systems. Risk-based water quality management is a new approach which has seen less effort developed to it so far. This area suffers from a lack of information and enough

data for analysis. To tackle this problem, fuzzy approaches have been used in a few studies but this area still needs more investigation. FWLAM is a tool on fuzzy decision making, and derives optimal fractional levels for the base flow conditions considering conflicting goals of the Pollution Control Agency (PCA) and dischargers. This tool has been used in several studies shown in Table 2.3 for the purpose of fuzzy modelling.

Table 2.3 Summary of the studies focused on risk analysis/uncertainty analysis/sensitivity analysis in water quality management in an IUWS

NO	Author(s)	Aim	Risk parameters	Risk/uncertainty modelling approach	Model
1	McIntyre & Zeng (2002)	Risk –based WQ ¹	Water quality parameters	MC ² and RSA ³	WaterRAT interface (spreadsheets)
2	McIntyre & Wheeler (2004)	DSS ⁴ for risk-based WQ	Water quality parameters	MC and RSA	WaterRAT interface
3	Sarang <i>et al.</i> (2008)	Risk- based WQ	DO, BOD, temperature and flow	FORM ⁵ and MC	QUAL2E-U model
4	Mc Avoy <i>et al.</i> (2003)	Risk-based IA ⁶ on WQ	-	Impact zone concept	QUAL2E-U model
5	Subbarao Vemula <i>et al.</i> (2004)	WQ-RA ⁷	DO and BOD	Fuzzy risk approach, SA ⁸ , FORM and MC	Fuzzy waste load allocation model (FWLAM)
6	Al-Redhwan <i>et al.</i> (2005)	Wastewater minimisation (i.e. cost minimisation) considering uncertainty	Operational uncertainties (concentration and flow)	Scenario-based approach	Mathematical Stochastic NLP ⁹ using CONOPT2 solver
7	Carrol <i>et al.</i> (2006)	Risk- based WQ	Water quality, Soil, Public health, Environmental	Failure scenarios related to OWTS developed	A logic model developed
8	Ghosh & Mujumdar (2006)	Minimize the risk of low water quality	DO and BOD	Fuzzy risk approach, FORA ¹⁰ , MC and SA	A risk minimization model developed
9	Wilby <i>et al.</i> (2006b)	REW ¹¹ -RA under CC ¹²	Physico-chemical, Biological and Hydro-morphological	Potential risk in WFD posed by CC	-
10	Dessai & Hulme (2007)	RA under CC	GHG ¹³ emissions, carbon cycle, climate impacts, global climate models	LSA ¹⁴ (one-at-a-time method)	HadCM3, UKCIP09
11	Schellart <i>et al.</i> (2008)	UA ¹⁵	DO and BOD	MC and SA (scatter plots)	Deterministic Integrated Catchment Modelling (ICM)
12	Sadiq <i>et al.</i> (2008)	RA-WQ	Water quality failures	Fuzzy probability, Fault tree analysis	Fuzzy model developed
13	Chiou (2008)	RA for WQ	Water quality parameters	Lifetime risk due to carcinogenic effects	Analysis based on the data collected
14	Brouwer & De Blois (2008)	UA-WQ	Water quality parameters	MC	RISK model (Excel_ Visual Basic)
15	Flores- Alsina <i>et al.</i> (2008)	UA	ASM parameters	MC	BSM2

NO	Author(s)	Aim	Risk parameters	Risk/uncertainty modelling approach	Model
16	Benedetti (2008)	RA- WQ	List of uncertain parameters considered by Benedetti (2006)	MC	Tornado tool (a new generation of the WEST_ product family)
17	Fu <i>et al.</i> (2009)	WQ	DO and AMM	RSA	SIMBA
18	Flores- Alsina <i>et al.</i> (2010)	EA ¹⁶ carried out by LCA ¹⁷	Water quality parameters	Multi-criteria matrix using multivariable statistical techniques A normalized Index of Risk based on a branch-decision scheme of decision-making theories	BSM2 ¹⁸
19	Grifoll <i>et al.</i> (2010)	RA-WQ	Water pollutions	Scenario-based, MC, SA (sensitivity index defined)	Sampled data, hydrodynamic models
20	Zhou <i>et al.</i> (2010)	EIA ¹⁹ -UA	Water quality parameters	Scenario-based GSA, MC	Sampled data
21	Sin <i>et al.</i> (2011)	IA	WWTP effluent concentrations, sludge production, energy demand	Aquatic risk based on Risk Quotient (RQ=MEC/PNE C)	BSM2
22	Vryzas <i>et al.</i> (2011)	RA-WQ	Water quality parameters	Weight of Evidence approach	Sampled data
23	Gottardo <i>et al.</i> (2011)	Integrated Risk Assessment (IRA) methodology -WQ	Environmental indicators: Biology, Chemistry, Ecotoxicology, Physico-chemistry, Hydromorphology	Generalised Likelihood Uncertainty Estimation (GLUE), MC	GIS-based Decision Support System, named MODELKEY DSS A mathematical model developed based on ASM1 and ASM2
24	Mannina <i>et al.</i> (2011)	UA	WWTP quality and quantity parameters	-	Data collected
25	Park <i>et al.</i> (2011)	Climate-induced risk analysis- WQ	Water quality parameters	-	-

1. WQ: Water quality assessment/management;
2. MC: Monte Carlo simulation;
3. RSA: Regional sensitivity analysis;
4. DSS: Decision support system;
5. FORM: First order reliability method;

6. IA: Impact analysis;
7. RA: Risk analysis/assessment;
8. SA: Sensitivity analysis;
9. NLP: Non-linear program;
10. FORA: First order reliability analysis;
11. REW: Review;
12. CC: Climate change;
13. GHG: Greenhouse gas;
14. LSA: Local sensitivity analysis;
15. UA: Uncertainty analysis;
16. EA: Environmental assessment;
17. LCA: Life cycle assessment;
18. BSM: Benchmark simulation model;
19. EIA: Environmental impact assessment.

2.5. IUWS Performance Optimisation

To have sustainable urban wastewater systems in terms of water quality (in addition to water quantity) under the future climate change and urbanisation, requires improving the system performance. For this purpose, optimisation algorithms are needed to assist water engineers to cope with these future challenges. The role of multi-objective optimisation has been investigated in several studies for improving the water systems. Pareto optimisation also has a direct role in decision-making at a management level, for example to illustrate the trade-off between economic costs and water quality improvements. This section reviews different optimisations applied to water systems to improve their performance in terms of water quality under the future changes.

RTC of urban wastewater systems has received much attention in the recent years in the academic literature. For the purpose of improving IUWS performance, RTC in urban wastewater systems aims to optimise the performance of the system under dynamic loading from rainfall. Considering this, Rauch & Harremoes (1999a) presented a novel approach to control the whole system: sewer system, treatment plant and receiving water with the aim to achieve minimum effects of pollution. With the methodology developed in this study, it is possible to optimise the system performance directly with respect to water quality parameters and to avoid the traditional indirect and artificial performance criteria (such as permissible annual overflow volume). The importance of this novel approach is illustrated by the fact that no stringent correlation has been found in investigation between the reduction of overflow volume and the increase of oxygen concentration in the receiving water.

Later on Schütze *et al.* (2004) reviewed the current state of the art of RTC of urban wastewater systems. Control options, not only of the sewer system, but also of the WWTP and of receiving water bodies are considered. Particular emphasis in this study is laid on methodologies of how to derive a control procedure for a given system.

With the application of integrated system modelling tools, overall system performance can be improved significantly in terms of receiving water quality, through development of optimal control strategies but up to now, most studies have used a single objective to demonstrate the potential benefits. For example

Zacharof *et al.* (2004) optimised the performance of the urban wastewater systems in an integrated modelling frame. This study aimed to identify the sites with high potential based on a river minimum dissolved oxygen concentration. For doing this purpose the model SYNOPSIS was used. The results showed that optimisation for DO performance did not necessarily reduce river ammonia concentrations and could in fact increase them. Widening the parameter space was shown to reduce the simplicity of the procedure and the correlation coefficients in the regressions.

Having said this, operational control of urban wastewater systems is actually a multiple objective optimisation problem, involving balancing different, possibly conflicting objectives required by stakeholders with different preferences and interests. Fu *et al.* (2008a) compared three different control strategies for multi-objective optimal control of the urban wastewater system, including one global control strategy and two integrated control strategies. A popular multiple objective evolutionary algorithm, NSGA-II, was applied to derive the Pareto optimal solutions for the three strategies. The comparative results show the benefits of application of integrated control in achieving an improved system performance in terms of dissolved oxygen and ammonium concentrations in the receiving river. The simulation results also illustrate the effectiveness of NSGA II in deriving the optimal control strategies with different complexities.

At the same time, Brdysa *et al.* (2008) optimised the operational control of integrated WWTP-sewer systems (IWWTS) by proposing an approach to designing the control structure and algorithms under a range of inputs. The model predictive controller is based on a dedicated grey box (GB) model of the biological processes and drawing its physical reality from the well-known ASM2d model. The optimised control of IWWTS allows for significant cost savings, satisfying the effluent discharge limits over a long period and maintaining the system in sustainable operation. The optimisation objectives in this study were: to minimise pollution load discharged to the receiver, to minimise plant running costs, to minimise emergency overflowing. The control system was implemented at a case-study in Poland to generate in RTC actions that were assessed by the plant operators and verified by simulation based on a calibrated plant model.

In addition to Fu *et al.* (2008b) and Brdys *et al.* (2008), the performance of an urban wastewater system was optimised in a study by Muschalla (2008). In this study an integrated pollution-load and water-quality model is combined with a multi-objective evolution strategy. The objective functions are investment costs and river water quality criteria and the decision variables in this study are both innovative and approved measures. The evaluation of water quality criteria was performed with regard to the frequency of critical concentrations in the river. The integrated simulation model required is provided by coupling a hydrological deterministic pollution-load model with a river water quality and a rainfall-runoff model. In this model the WWTP are simplified for simulation. The practice of the optimisation and simulation tool has been validated by analysing a real catchment area including sewer system, WWTP, water body and natural river basin.

Following the aforementioned study by Fu *et al.* (2008b), the integrated modelling perspective was applied by Fu *et al.* (2010) to investigate the optimal distribution and control of storage tanks with an objective to mitigate the impact of new residential development on receiving water quality. The traditional approach determined the distribution of storage tank volume in the sewer system by separately modelling of that. In this study, the cost of storage tank construction, and two receiving water quality indicators, dissolved oxygen and ammonium concentration, are used as the optimisation model objectives and performance feedback. The optimal storage distribution resulted in this study shows the benefits of direct evaluation of receiving water quality impact in an integrated framework.

In addition to the operational control optimisation, design of the IUWS needs to contribute to the system performance improvement. For example Alvarez-Vazquez *et al.* (2008) addressed the optimal design (outfall locations) and optimal operation (level of oxygen discharges) of a wastewater treatment system. This problem was formulated as a two-objective mixed design and optimal control problem with constraints on the states and the design and control variables. The two-objective problem is formulated as a single-objective problem through the use of the weighted sum method. The existence of the optimal solution is then demonstrated for an arbitrary set of weights and a first

order optimality condition is obtained to characterize that solution. A realistic case study posed in the ría of Vigo was used in this study.

Another optimisation approach was applied by Rivas *et al.* (2008). They presented the mathematical basis and some illustrative examples of a model-based decision-making method for the automatic calculation of optimum design parameters in modern WWTP. This study aims to show how the proposed methodology is able to achieve optimum WWTP design using either a steady-state or dynamic mathematical model of the plant and a set of constraints associated with the permitted operational ranges and the required water quality in the effluent. The design parameters are calculated as a Mathematical Programming (Optimisation) Problem that can be solved using a non-linear optimisation algorithm (GRG2). The effectiveness of the proposed methodology is investigated by the optimum design of the Step-Feed process for nitrogen removal (Alpha) considering two different problems: the optimum plant dimensions, estimated at critical temperature for effluent requirements (Problem 1), and the optimum selection of facultative volumes, fractions of the influent flow-rate and the values of oxygen set-points for long-term plant operation (Problem 2). The proposed decision-making method helps engineers involved in the design of new complex WWTP to select the main design parameters.

A new interactive tool was developed for WWTP design by Hakanen *et al.* (2011). This tool utilises interactive multi-objective optimisation which enables the designer engineers to consider the design with respect to several conflicting evaluation criteria simultaneously. This design improvement is important as the WWTPs need to see different criteria such as environmental and economical. By combining a process simulator to simulate wastewater treatment and interactive multi-objective optimisation software to support the designer during the design process, we obtain a practically useful tool for decision support. The applicability of this tool is illustrated with a case study related to municipal wastewater treatment where three conflicting evaluation criteria are considered.

The multi-objective optimisation approach, in addition to the operational control and design optimisation, is applied for other purposes. In line with this, Vojinovic *et al.* (2005) oriented towards resolving inadequate representation of systems complexity, incorporation of a dynamic model into the decision-making loop, the choice of an appropriate optimisation technique and experience in applying a

new approach for the optimisation of wastewater systems remedial works requirements. In this study it is proposed that the optimal problem search is performed by a global optimisation tool (with various random search algorithms) and the system performance is simulated by the hydrodynamic pipe network model. The work on assembling all required elements and the development of appropriate interface procedures between the two tools, aimed to decode the potential remedial solutions into the pipe network model and to calculate the corresponding scenario costs, is currently underway.

Additionally Tudor & Lavric (2011) addressed the dual-objective optimisation of an integrated water/wastewater network (IWWN) by targeting minimum fresh water consumption at the same time as operating costs reduction. An IWWN is a recycle system composed of two oriented graphs, the first encoding the water-using units (WUs) and the second, the treatment units (TUs). The corresponding mathematical model was written. In this study a synthetic example is proposed and analysed under several scenarios with respect to the fresh water consumption, the magnitude of internal and treated water reuse and the investment/operating costs related to the active pipes network.

In addition to abovementioned study, Lim *et al.* (2010) developed a mathematical model to integrate and optimise urban water infrastructures for supply-side planning and policy: freshwater resources and treated wastewater are allocated to various water demand categories in order to reduce contaminants in the influents supplied for drinking water, and to reduce consumption of the water resources imported from the regions beyond a city boundary. The integration and optimisation in this study decrease (i) average concentrations of the influents supplied for drinking water, which can improve human health and hygiene; (ii) total consumption of water resources, as well as electricity, reducing overall environmental impacts; (iii) life cycle cost; and (iv) water resource dependency on other regions, improving regional water security. The model developed contributes to sustainable urban water planning and policy.

For the purpose of optimisation, different methods and approaches can be used. Evolutionary algorithms like Genetic Algorithms (GA) are the most common and have been applied in many water engineering optimisations. A GA is a stochastic search algorithm that applies the biological concept of survival of

the fittest in order to search for the optimal solution to a problem. The potential and the benefit of using GAs for solving problems in urban drainage modelling were investigated in a study by Rauch & Harremoes (1999b). In a review in this study, the advantages of traditional optimisation procedures with recent methods were identified in model calibration and model predictive control. They were implicitly expressed that the use of GAs for multi-criteria decision analysis is an interesting field of application. The methodology is discussed by means of benchmark problem sets for each of the applications.

In line with the application of GAs for the IUWS performance optimisation, Heon Choa *et al.* (2004) developed an optimisation model which is implemented by integration of GA and a mathematical water quality model. The objectives in this model are to achieve water quality goals and optimizing the wastewater treatment cost in a river basin. For doing this purpose, the Arc/View GIS database is applied and the pollution source, land use, geographic features and measured water quality data of the river basin are incorporated. The cost is calculated on the base of treatment type and treatment cost for each WWTP in the river basin. Four scenarios that do not use the GA were proposed and they were compared with the results of the management model using the GA. It was clearly observed that the results based on the GA were much better than those for the other four scenarios from the viewpoint of the achievement of water quality goals and cost optimisation.

Also GA optimisation was applied by Lavric *et al.* (2005) to water systems with multiple contaminants and several contaminated sources. The objective function in this study is the total supply water consumption, which should be minimised. This approach generates the overall optimal water network topology with respect to the minimum supply water usage, complying, in the same time, with all restrictions. The mathematical model describing the unit is based upon total and contaminant species' mass balances, together with the input and output constraints.

Later on Fang *et al.* (2011) combined an extended model derived from ASM no. 3 to simulate the biological nutrient removal in anaerobic–anoxic process in a full-scale WWTP. The accelerating genetic algorithm (AGA) approach is used to optimize the operating conditions by taking into account the effluent quality. The results demonstrate that the integration of the mechanistic model and AGA

approach is an effective strategy for the optimization of complex biological processes.

Following the recent emphasises on the necessity of considering sustainability in water systems (UNESCO, 2011), the risk concept and inherent uncertainty in the IUWS components to improve the IUWS performance may help engineers and water planners to better cope with the future changes. In line with this, a methodology for evaluation of risk for a river water quality management problem was presented by Subbaro Vemulal *et al.* (2004). In this study a fuzzy waste load allocation model is solved with a simulation–optimisation approach for obtaining optimum fractional removal levels for the dischargers to the river system. The event of low water quality at a checkpoint in a river system is considered as a fuzzy event, with suitable membership functions defined for the fuzzy risk of low water quality.

Later on Al-Redhwan *et al.* (2005) optimised water networks in process industries considering uncertainty. Because of the fact that wastewater flow rates and the levels of contaminants may vary widely as a result of changes in operational conditions and/or product specifications, optimal wastewater network designs should be resilient and able to handle such changes.

Additionally Flores-Alsina *et al.* (2010) showed the benefits of complementing the environmental assessment carried out by life cycle assessment with economical e.g. operation costs, technical e.g. risk of suffering microbiology-related TSS separation problems and legal criteria e.g. achievement with the effluent standards in terms of the different pollution loads. Using a preliminary version of the BSM2 as a case study, different combinations of controllers are implemented, simulated and evaluated.

Combining the optimisation techniques with the risk-based water quality management is a quite new approach. Regarding this a risk minimisation model was developed by Ghosh & Mujumdar (2006) to minimise the risk of low water quality along a river in the face of conflict among various stake holders. The model consists of three parts: a water quality simulation model, a risk evaluation model with uncertainty analysis and an optimisation model. Fuzzy multi-objective programming is used to formulate the multi-objective model. Results of the models are compared with the results of a deterministic fuzzy waste load

allocation model (FWLAM), when methodologies are applied to the case study of Tunga–Bhadra river system in southern India, with a steady state BOD–DO model.

Table 2.4 shows a summary of the studies used risk-based and non-risk-based optimisation approaches so far to improve the IUWS performance in terms of mostly water quality criteria. As can be observed, in addition to water quality indicators (as the optimisation objectives) operation and design costs are dominant criteria. This is of great importance as adapting the IUWS under the future changes will need appropriate investments and therefore considering the cost of these adaptations (as an optimisation objective) is important. This can help water planners to have accurate estimates of the budget required in the future for the systems development.

Most efforts so far have been done on improving the operation of the IUWS rather than the design and only Alvarez-Vazquez *et al.* (2008) made an effort to combine both operation and design to improve the performance of the only wastewater treatment system. As noted in the aforementioned study, the approach applied is a new one and extending that to an integrated context has the potential to upgrade the systems (in terms of design and operation) considering the existing interactions among the sewer systems with WWTP and river with WWTP. This probably can give a better estimation of the budget required to adapt the systems for the future changes.

Depending on the type of the optimisation, the decision variables can change. As can be observed in Table 2.4 different methods, tools and approaches are applied for the purpose of the optimisation. The majority of the studies apply a deterministic approach in optimisation and it seems GA or GA-based approaches are dominant for the purpose of optimisation such as a NLP model developed by Alvarez-Vazquez *et al.* (2008) for optimisation.

Also as it can be observed in Table 2.4 only few studies have focused on the risk-based optimisation of the IUWS. Those which have applied the aforementioned approach have used a fuzzy approach for this purpose. A clear gap in the literature is therefore noted in applying risk-based optimisation as a way to adopt urban wastewater systems to future changes.

Table 2.4 Summary of the studies focused on IUWS performance optimisation

NO	Author(s)	Optimisation Criteria	Type of the optimisation	Decision variables	Optimisation /simulation tools	Case Study
1	Rauch & Harremoes (1999a)	WQ ¹ calibration	Operational	Urban drainage operational parameters	GA ²	BSM ³
2	Heon Choa <i>et al.</i> (2004)	WQ, wastewater treatment cost	Operational	Wastewater treatment operational parameters	GA, QUAL2E	Youngsan River in Korea
3	Zacharof <i>et al.</i> (2004)	WQ, RTC ⁴	Operational	$Q_{maxin}^5, Q_{maxout}^6, Q_{trigst}^7, \dots$	SYNOPSIS, GA	(Schütze, 1998)
4	Subbaro Vemulal <i>et al.</i> (2004)	WQ	Operational	WWTP control parameters	FWALAM ⁸ , GA, QUAL2E	Tunga–Bhadra river
5	Lavric <i>et al.</i> (2005)	WQ and water consumption	Operational	Inflow and outflow, contaminant Water demand,	GA, a mathematical simulation model	Hypothetic
6	Al-Redhwan <i>et al.</i> (2005)	WQ, Cost	Operational and design	maximum allowable inlet and design outlet concentration	Stochastic and Deterministic NLP ¹¹ optimisation algorithm	4 case studies data collected
7	Ghosh & Mujumdar (2006)	Fuzzy Risk-based WQ	Risk of low water quality	Fractional removal level	FWALAM	Tunga–Bhadra river
8	Fu <i>et al.</i> (2008)	WQ	Operational	$Q_{maxin}, Q_{maxout}, Q_{trigst}, \dots$	NSGA-II, SIMBA	(Schütze, 1998)
9	Alvarez-Vazquez <i>et al.</i> (2008)	WQ, Cost	Operational and design	Outfall location and level of oxygen discharges	A global NLP solver	ría of Vigo
10	Rivas <i>et al.</i> (2008)	WQ	Design	Plant dimensions, facultative volumes	Non-linear optimisation algorithm (Generalized Reduced Gradient algorithm)	Alpha process
11	Fu <i>et al.</i> (2010)	WQ, Cost	Operational	Distribution of storage tank volume in the sewer system	NSGA-II, SIMBA	(Schütze, 1998)
12	Muschalla (2008)	WQ, investment cost	Operational	Measures of water quality indicators	An integrated simulation-optimisation modular developed	River Bieber catchment in Germany
13	Flores-Alsina <i>et al.</i> (2010)	WQ, Cost	Operational	Different combinations of controllers	BSM2	BSM2

NO	Author(s)	Optimisation Criteria	Type of the optimisation	Decision variables	Optimisation /simulation tools	Case Study
14	Brdysa <i>et al.</i> (2008)	WQ, Cost, CSO ⁹	Design	Air supply to aerobic zones, inflow rates, sludge flow rate, tanks filling/emptying rate	ASM2 ¹⁰ , An optimisation algorithm developed	Kartuzy IWWT system located in Poland
15	Flores-Alsina <i>et al.</i> (2010)	WQ, Cost	Operational	Different combinations of controllers	BSM2	BSM2
16	Lim <i>et al.</i> (2010)	WQ, Cost	Operational		Mathematical model developed	Ulsan metropolitan city in Korea
17	Hakanen <i>et al.</i> (2011)	WQ, Cost	Design	Operational parameters	ASM, interactive multiobjective optimisation	WWTP
18	Fang <i>et al.</i> (2011)	WQ	Operational	Operational parameters	Integration of the mechanistic model and accelerating GA (AGA)	ASM3
19	Tudor & Lavric (2011)	Water consumption, investment/operating cost	Operational	Operational parameters	A mathematical developed	Synthetic example

1. WQ: Water quality assessment/management;
2. GA: Genetic algorithm;
3. BSM: Benchmark simulation model;
4. RTC: Real time control;
5. Q_{maxin} : Maximum inflow to the WWTP;
6. Q_{maxout} : Maximum outflow from the sewer system;
7. Q_{trigst} : Threshold triggering the storm tank;
8. FWALAM: Fuzzy waste load allocation model;
9. CSO: Combined sewer overflow;
10. ASM: Activated Sludge Model;
11. NLP: Non- linear programming.

2.6. Summary

In this chapter, a literature review relevant to a deterministic and risk-based optimisation of the operational control and design of the IUWS under climate change and urbanisation was presented.

Firstly, in section 2.2, studies that focus on the integrated modelling of the urban wastewater systems aiming at water quality management from different perspectives were presented. In this section the pros and cons of the integrated modelling of the urban wastewater systems were discussed. Finally it was concluded that for more precise impact assessment in urban wastewater systems, applying the integrated approach has the potential to represent more accurate and reliable results under future changes.

Secondly, in section 2.3, the impacts of climate change and urbanisation on IUWS performance were reviewed and discussed. In this section specifically the potential impacts of climate change, urbanisation and their combined impacts on river water quality were reviewed. Also different approaches (e.g. scenario-based) and models used for climate change and urbanisation modelling were presented. The findings in this section demonstrated the accuracy of the results obtained but noted that combined modelling approaches were less common.

Thirdly, in section 2.4 the significance of considering risk and uncertainty in water quality analysis were discussed. In this section the importance of sensitivity analysis was emphasised to recognise the most uncertain parameters under climate change and urbanisation. In line with this, different GSA methods applied in recent studies were presented. In this section the impact of risk analysis on water quality management was discussed. It was concluded that to achieve more sustainable IUWS under future changes, it was important to consider the concept of risk, its assessment and management. Therefore with regard to the focus of this study on water quality management in the future chapters, the risk of water quality failures will be integrated as a suitable optimisation objective. The findings in this section will be applied later in Chapters 4 and 7.

Finally, in section 2.5 the impacts of optimisation techniques to improve water systems performance (especially in IUWS) were discussed. In line with this, deterministic optimisation of the IUWS operation and also design were

investigated. Meanwhile in addition to water quality indicators, cost was considered as another optimisation objective. Additionally a few studies applied a stochastic approach in water quality optimisation. What can be really highlighted here for more investigation (under future climate change and urbanisation) is the application of risk-based approaches in water quality improvement in an IUWS. Additionally in line with this there needs to be a comparison between risk-based with non-risk-based approaches in water quality improvement. This comparison will help decision makers to improve the level of performance in IUWS under the unavoidable future changes. The studies in this section will be applied later in Chapters 5, 6 and 7.

CHAPTER 3

INTEGRATED URBAN WASTEWATER SYSTEM MODELLING

3.1 Introduction

With reference to the aim of this thesis in Chapter 1, the system is investigated through the lens of an IUWS perspective. Therefore the urban wastewater system is considered as a whole comprising of the sewer system, WWTP and receiving water bodies. In this chapter the aim is to introduce the methodology used to model the IUWS, together with the case study used throughout this thesis.

The advantages of integrated analysis of the urban wastewater systems have been addressed by Schütze *et al.* (2002a), Schütze *et al.* (2002b), Schütze *et al.* (2004) and Zacharof *et al.* (2004). Butler & Schütze (2005) also demonstrated theoretically that a significant improvement in performance of the system can be achieved by the integrated real time control as it considers the interactions between different components of the system. So far there are only a few practical examples of any scale (Butler & Davies, 2011) although integrated analysis of the urban wastewater systems is firmly in line with the precepts of the EU WFD (Kallis & Butler, 2001). This approach has typically been applied so far with the motivation of improving the performance of the whole system by real time control, based on achieving appropriate receiving water quality criteria (Vanrolleghem, *et al.*, 2005; Fu, *et al.*, 2008a).

In section 3.2 the tool used for simulating the IUWS and the approaches applied to simulate the IUWS processes and components (including sewer system, WWTP and river) are introduced. The IUWS modelling methodology presented

in this chapter is demonstrated on a case study. Details about this case study are introduced in section 3.3. This case study will be used throughout the thesis to analyse the impacts of climate change and/or urbanisation and to identify the associated best course of actions to mitigate the negative impacts of the two.

With regard to the approach propounded in this thesis (referenced to Chapter 1), the operational control performance of the existing IUWS and with the current settings of the operational controlling parameters, are evaluated in terms of DO and AMM concentrations in the receiving water under the base rainfall case. This is done in section 3.3.2. These evaluations represent the BC performance in meeting the DO and AMM concentrations standards. Also these evaluations will be compared with the impacts of climate change and/or urbanisation on performance of the IUWS in Chapter 4 and Chapter 5 to show the potential required to improve the BC to cope with these future changes. There is a summary of the results of this chapter in section 3.4.

3.2 IUWS Model

The simulation tool of the IUWS studied here is based on the SIMBA5 simulation tool, developed by IFAK (2005). SIMBA5 consists of a library of modelling blocks (using the Matlab/Simulink Framework) to simulate different individual components of the urban wastewater system (see Figure 3.1). SIMBA was chosen due to its flexibility as an open simulation environment, allowing wastewater treatment plants, sewer systems and rivers to be modelled in parallel, together with information exchange across the sub-models. In addition, SIMBA has been used in earlier studies by the group and good contacts are kept with IFAK.

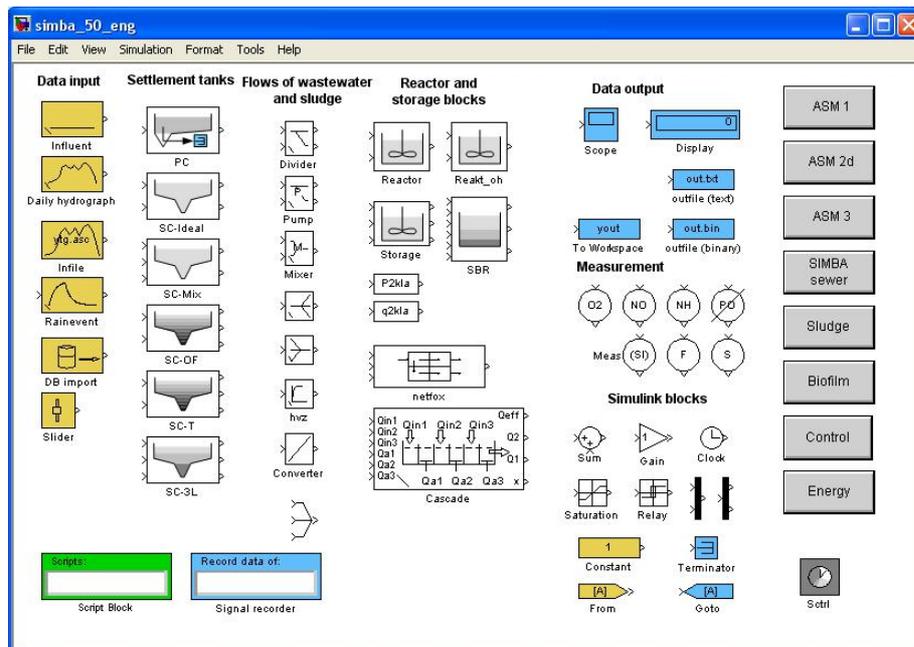


Figure 3.1 SIMBA5 front page and blocks' library

In each subsystem in this software, various hydraulic, hydrologic, hydrodynamic and biochemical processes are considered which provides the possibility of considering the dynamic interaction of each component in the system. The outputs of SIMBA5 are the wastewater flow rates and pollutant concentrations in all subsystems. From the block libraries provided, the user selects blocks corresponding to the main elements of the system to be modelled, connects them by flow and information links and can start the simulation within a fairly short time. By adding the block SIMBA Sewer, relevant blocks for WWTP and receiving water body (SIMBA Sewer block), an IUWS can be set up. Such a model includes full consideration of all interactions between its component parts and thus allows integrated simulation and operational control studies to be carried out in a convenient way.

3.2.1 Sewer System Modelling

The SIMBA Sewer block is used for the simulation of sewer systems (see Figure 3.1). SIMBA provides the choice between two approaches of sewer system modelling concepts, differing in their level of complexity-simplified (hydrological) and detailed (fully hydrodynamic) modelling approaches. With regard to this, the hydrologic approach is applied for the simulation of sewer networks in this study because of the unimproved computational speed. The modelling approaches have been used in the sewer network simulation can be outlined as the following:

- Rainfall-runoff;
- Dry weather flow (DWF);
- Catchment;
- Flow by translation;
- Storage tanks and overflow structures.

The rainfall runoff modelling has been considered for impervious and pervious areas of the catchment. For this purpose, the KOSIM approach has been applied here (the only existing option in this version of SIMBA). In this study the rainfall runoff simulation wetting losses, depression storage losses, wash-off, infiltration and evaporation losses are taken into account and assumed to be constant.

Surface runoff and flow within the sewer network are modelled conceptually by Nash Cascades (Nash, 1958) and by translation (Cascades of linear reservoirs), as shown in equations (3.1)-(3.3). Due to the simplicity of Nash Cascade approach, rapid simulation is facilitated. Equations (3.1)-(3.3) show the Nash Cascades to model the surface runoff and flow within sub-catchments. N series of identical (conceptual) tanks are considered to attenuate the flow. Each of the n reservoirs in series can be described by the storage equation as equation (3.1):

$$\frac{dS(t)}{dt} = I(t) - Q(t) \quad (3.1)$$

And the continuity equation (relating outflow to storage) as equation (3.2),

$$S(t) = KQ(t) \quad (3.2)$$

where, $I(t)$: inflow at time t (m^3/s); $Q(t)$: outflow at time t (m^3/s); $S(t)$: storage at time t (m^3); K : storage constant (s). The flow time of the centre of gravity of the input (t_L) is shown in equation (3.3),

$$t_L = n \times K \quad (3.3)$$

Where, n : number of conceptual reservoirs (m^3); K : storage constant (s).

Pollutants in the catchment originate from two sources: DWF and rainfall runoff. The concentrations of pollutants in these two have been considered constant. A

diurnal pattern of flow and pollution for DWF simulation has been considered in the sewer system including a number of pollutants (SS, VSS, AMM, nitrate etc).

In the hydrological approach applied, whilst flow on the surface and within sub-catchments is described by Nash cascades, flows between sub-catchments are described by constant flow times (special blocks have been provided for this purpose).

The storage tanks are modelled in this study by blocks provided with regard to the type of the storage tanks applied (on-line or off-line, by-pass or pass-through). In the storage tanks considered in this study, the maximum throttle flow, maximum overflow rates, storage tanks' volumes are indicated. The storage tanks' performance is modelled based on a simple sedimentation approach and without any biological processes allowing reduction of pollution in overflows to be modelled.

3.2.2 Wastewater Treatment Plant Modelling

SIMBA5 allows the simulation of biological WWTPs, particularly the Activated Sludge processes. The ASM1 model established by the IWA work group (Henze, *et al.*, 1986) is the model used in this study for operational control and process studies of biological WWTPs (Henze, *et al.*, 1986). Also the IWA Task Group (Copp, 2002) has applied it in the BSM1.

The considered WWTP in this study is an aerobic WWTP including storm tank, primary clarifiers, secondary clarifiers, reactors and pumps. To model and simulate each subsection the following approaches are applied:

For modelling the storm tank the same approaches as the storage tanks in the sewer system is applied. The purpose of primary clarification is to remove settleable solids. Typically 50 to 70% of the total suspended solids are removed in this process. Since some of the solids are biodegradable, BOD is reduced by 30 to 40%. In this study the clarifier is considered as a completely mixed reactor. In addition to the active capacity of the primary clarifier the biodegradable removal is assumed about 70% for this study.

A completely mixed nitrifying reactor based on the ASM1 with oxygen input by pressure aeration is applied in this study. Therefore the reactor volume, oxygen transfer rate, immersion depth and temperature values are set to constant values for this purpose.

The secondary clarifier is an integral part of the activated sludge system. It has two main functions: it separates the biomass from the water in order to produce a good quality effluent free of settleable solids and the biomass is thickened (thickening). Part of the biomass is then wasted as sludge and part of it is returned to the biological reactor to maintain an appropriate biomass concentration. The volume of this reactor is structured into 3 horizontal layers. The top layer models the clear water zone during the settlement phases, a variable volume centre layer to model the sludge thickening and storage and fixed volume bottom layer to model the bottom sludge concentration. The sludge flow (return or wastage) is removed from the bottom layer. The surface area, height, sludge volume index and mixing flow ratios of the reactor are set to values in the reactor modelling. Also the temperature is applied to that as well. Two pumping stations have been considered in the WWTP to return the activated sludge to the reactor and also to control the wastewater influent to the WWTP.

3.2.3 River Modelling

The water recipient (river) in SIMBA is modelled within the Sewer block (see Figure 3.1). For Hydrodynamic flow routing (saint-Venant equations), SIMBA uses the public domain package EPA Storm Water Management (SWMM5) available from the US EPA (Rossman, 2004) as a block for modelling the river. This block can be parameterised to exchange data with the SIMBA simulation model. By default, output signals describing all system outflows (to WWTP and CSO) are generated. The behaviour of the sewer network can be influenced by a configurable set of input ports.

In this study the SWMM software (from SIMBA Sewer block) is applied for water flow modelling (Hydrodynamic approach). For the purpose of water quality modelling in the river the water quality model developed by Lijklema *et al.* (1996) as presented by Schütze (1998) was applied. The river water quality model incorporates a number of processes (including among others re-aeration, decay of organic matter, nitrification etc.) affecting DO, AMM and COD concentrations in the river. Finally linking water flow and quality models for sewer systems, treatment plants and receiving water bodies, as well as for other parts of the urban wastewater systems, allows the wastewater system to be considered as one unit. Dealing with conversion of the pollutants between

each subsystem is a challenge in the context of integrated modelling. In SIMBA a factor-based conversion method described by Schütze (1998) is used here to convert different pollutants. The actual parameters (i.e. the IUWSM input variables) used to quantify the impact of urbanisation and climate change on the recipient's water quality are described in Chapter 4.

3.3 Case study

3.3.1 Description

The schematic diagram of the case study used in this thesis is shown in Figure 3.2. This case study was originally defined by Schütze (1998) and has been studied for various purposes, including RTC (Butler & Schütze, 2005; Fu, *et al.*, 2008b), system RTC potential analysis (Zacharof, *et al.*, 2004) and system impact analysis (Lau, *et al.*, 2002). As Figure 3.2 shows, the IUWS is divided into three main parts comprising a sewer system, a wastewater treatment plant and a river.

The sewer system analysed here is an example sewer system discussed, reported and used by ATV-A128 (1992). This example has been used in a number of other studies involving KOSIM sewer system model. Additionally ATV-A128 is a German guideline and standard commonly applied for the design and operation of sewer systems without detailed consideration of the other elements of the urban wastewater system.

The hydrological approach introduced in section 3.2.1, has been used in this case study for modelling the sewer system. It has seven sub catchments (SC1-SC7) with a total area of 725.8 ha. There are four on-line pass-through storage tanks, located at the downstream of sub-catchments SC2, SC4, SC6 and SC7. The outflow of each of these four tanks is controlled by a pump. A storage tank (on-line pass through tank) with the capacity of 7000 m³ (the storage tank in SC7) is located at the inlet to the wastewater treatment plant (in SC7). The considered storage tank in SC7 is used to control the CSO and store the wastewater in excess of the capacity of the wastewater treatment plant by a pumping system. Thresholds (maximum and minimum) have been considered for controlling the storage tank release in SC7 and this is fixed for the other storage tanks (in SC2, SC4, SC6) to a value.

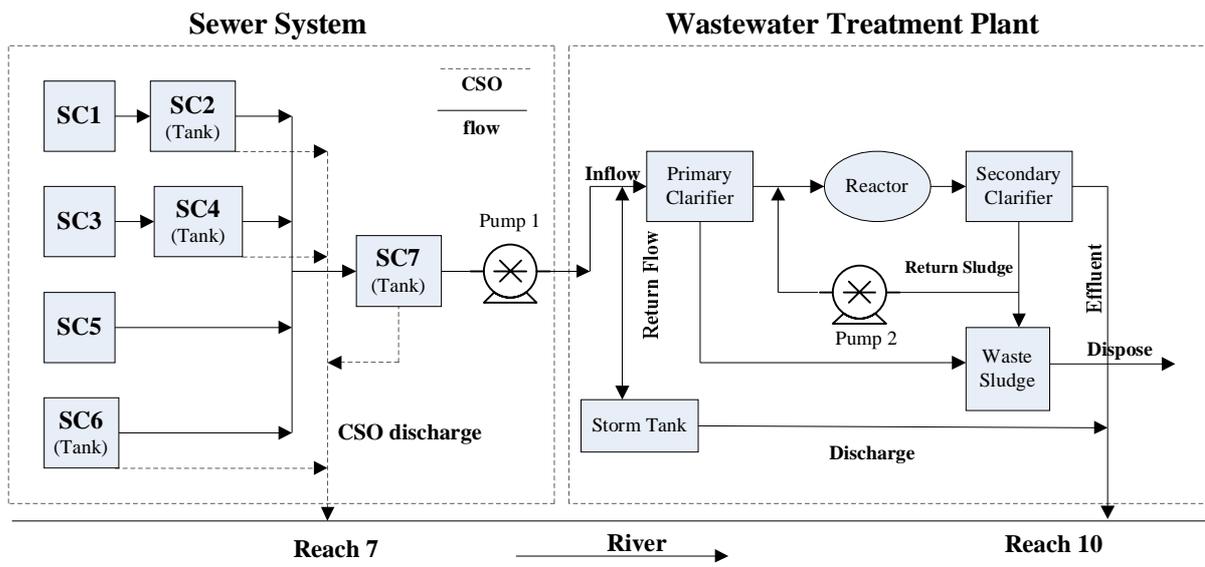


Figure 3.2 Schematic diagram of the case study of IUWS (semi-hypothetical case study)

Lessard (1989) provided a dataset for concentration of different water quality indicators for DWF and storm water which are applied for the sewer system in this study. These concentrations for DWF and storm water (i.e. wet weather flow - WWF) in this case study are as follows:

1. DWF: SS: 335 mg/l; VSS: 245 mg/l; COD: 606 mg/l; soluble COD: 281 mg/l; ammonium: 27.7 mg/l; nitrate: 0;
2. WWF: SS: 190 mg/l; VSS: 139 mg/l; COD: 100 mg/l; soluble COD: 46 mg/l; ammonium: 2 mg/l; nitrate: 0.

The wastewater treatment plant is based on the Norwich sewage networks in eastern England and was studied in detail by Lessard & Beck (1993). This treatment plant has the capacity to treat an average DWF of 27,500 m³/d and consists of a storm tank, primary clarifier and activated sludge reactor and secondary clarifier. The wastewater led into the storm tank is allowed to settle in the tank and then settled wastewater is discharged into the river whenever storm tank overflow occurs. The tank with 6750 m³ storage capacity is an offline pass through storm tank, in which the particulate pollutants may settle before discharged to the receiving river when overflows occur during rain events. This provides additional storage to that of the tanks in the urban wastewater system.

Filling of the storm tank is controlled by the maximum inflow rate to the primary clarifiers. The tank is emptied at a pump rate, as soon as the inflow rate to the

plant drops below a pre-specified threshold value. These two flow rates are set by the control module which also controls the maximum inflow rate to the primary clarifiers. The waste and return activated sludge flows are taken from the secondary clarifiers and their flow rates are set to 660 m³/d and 14400 m³/d respectively.

In order for a data set to be appropriate to the calibration and verification of the IUWS, it would ideally have been collected from sewer system, WWTP and the receiving river of the same case study site at the same time (including dry weather and rain periods). Such a data set of flow and relevant pollution parameters would be useful for the description of the behaviour of the IUWS. Since these data were not available in the early stages of this study, no detailed analysis as to whether these are appropriate for use in this study could be conducted. Therefore in many integrated modelling studies reported, a large proportion uses hypothetical data for parts of the IUWS. For these reasons, this study has to be based on a semi-hypothetical case study site. Therefore it is obvious that such a site should resemble the behaviour of a real system as closely as possible. In line with this, for the sewer system, the example reported by ATV-A128 (1992) is used. The WWTP is based on the Norwich WWTP in the UK. The wastewater treatment plant model has been previously calibrated and validated (Lessard & Beck, 1993). Finally in the following of the aforementioned reasons, a purely hypothetical river is defined.

The river system is hypothetical and a 45 km long stretch has been simulated, divided into 45 equal reaches. Reach 10 is located about 1 km downstream of the treatment plant effluent, reach 30 is located almost in the middle and reach 40 at the downstream of the river. The river base flow is 129,600 m³/d resulting in a 1:5 dilution ratio of dry weather treatment plant discharges to river base flow. Runoff generated by rainfall on the upstream catchments enters the system as an additional inflow into the river at reach 1. The CSOs are assumed to discharge at reach 7 with the storm tank overflows and treatment plant effluent at discharging reach 10. The initial and boundary conditions of the water quality indicators (Schütze, *et al.*, 2002a) are: NH₄: 0.09 mg/l, DO: 9 mg/l, slowly biodegradable BOD: 1.8 mg/l and readily biodegradable BOD is set to zero, assuming that the organic material has biodegraded upstream of the treatment plant effluent and CSO discharges.

3.3.2 System Performance in the Base Case

As will be shown in Chapter 5 a number of cases corresponding to different future climate and urbanisation changes will be considered in this thesis. Here, the so called BC is introduced. In this case, the system is assumed to function under existing conditions, i.e. without any climate or urbanisation related changes. In the BC, the IUWS described above is subjected to a six-day rainfall event from 7-13th February 1977 with a total depth 27 mm and with the return period of 11 year, as shown in Figure 3.3. This rainfall is named the base rainfall in this study. Five operational control parameters defined by Schütze (1998) from the sewer system and treatment plant, shown in Table 3.1, are chosen for system operational control.

Table 3.1 Operational control parameters in the BC (Schütze, 1998)

Description	BC value
Maximum outflow rate of the storage tank linked to sub-catchment 7	5× DWF*
Maximum inflow rate to treatment plant	3×DWF*
Threshold triggering emptying the storm tank (m ³ /d)	24192
Emptying flow rate of storm tank (m ³ /d)	12096
Return activated sludge rate (m ³ /d)	14688

*This is an average DWF (27,500 m³/d) in the BC that can be treated in the WWTP everyday

The base rainfall causes some CSO discharges under the current settings of the operational control parameters as shown in Figure 3.3. As it can be observed in Figure 3.3, at the peak of the base rainfall event, the IUWS reaches to the maximum influent to treatment and this brings about CSO discharges into the river. After a few days of the rainfall (i.e. about 12 Feb) although there is another peak (but smaller than the first peak) in the rainfall event but no CSO discharges can be observed. This shows that 4 days time between the aforementioned two rainfall peaks can provide enough opportunity in the system to control the CSO discharge. Combined sewer systems are widely the used in urban areas to collect and convey both DWF and storm water runoff through a single pipe system to wastewater-treatment plants. One planned outcome of such systems is the intermittent direct discharge of CSO structures to receiving waters when flow exceeds the available system capacity. CSO discharges can contain pollutants, such as organics, sediments, microbial pathogens, nutrients, and toxics, and have been identified as a significant contributor to receiving

water pollution and human health impacts (EPA., 2008; Even, *et al.*, 2007; Fu & Kapelan, 2010). Therefore with regard to the considered approach in this study, CSO discharges which have the potential to deteriorate the quality of water in the rivers according to the studies by Chen *et al.* (2004), Butler & Davies (2011) and Even *et al.* (2007) are presented in Figure 3.3 in the BC.

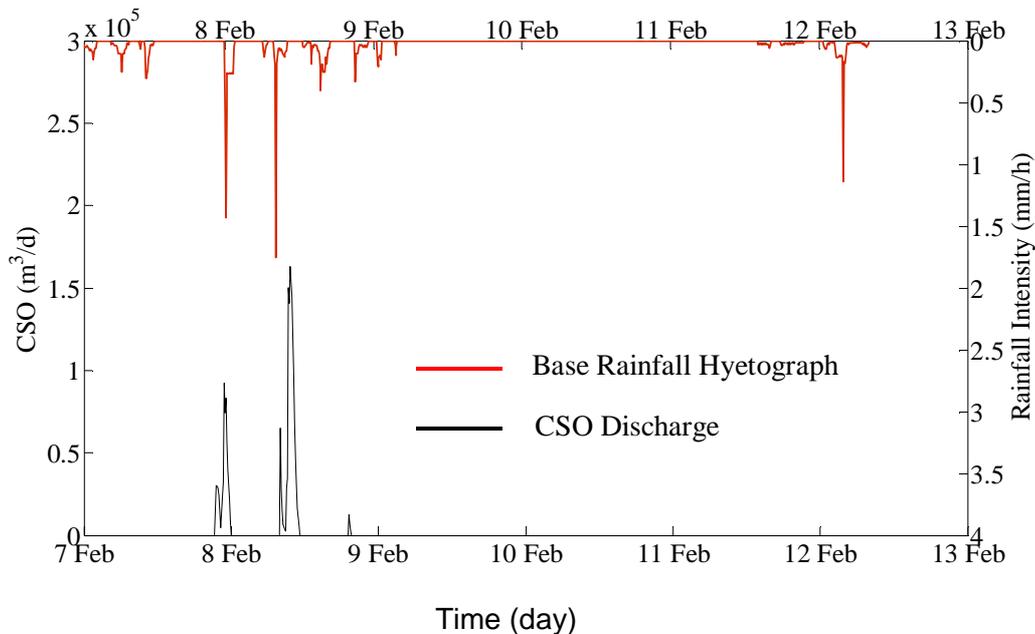


Figure 3.3 Base rainfall Hyetograph and CSO discharge

The DO and AMM concentrations obtained for the base rainfall event are presented (at various reaches of the river shown in Figure 3.4) in Figure 3.5a and Figure 3.5b respectively. These two parameters are used as indicators of the water health for the aquatic life in the river. The threshold value of 4 mg/l is used here as an environmental standard for the DO and AMM in the river (FWR, 1998; Schütze, *et al.*, 2002a; Fu, *et al.*, 2009). Any violation from these standards is interpreted as a failure of the IUWS and potentially harmful to the aquatic life.

Under the BC controllers settings (as shown in Table 3.1), the minimum DO concentration and maximum AMM concentration are approximately 3.60 mg/l and 3.35 mg/l respectively. As can be observed from Figure 3.5a, the DO concentration at the downstream end (reach 40) drops below a 4 mg/l threshold. Therefore it can be concluded that under the base rainfall (and the current operational control strategy in the BC) DO concentration in the river breaches to the water quality standard. Also Figure 3.5b shows that, AMM

concentration is below the 4 mg/l in all the reaches of the river. Therefore as a result the current controlling strategy in the BC meets the AMM concentration threshold under the base rainfall.

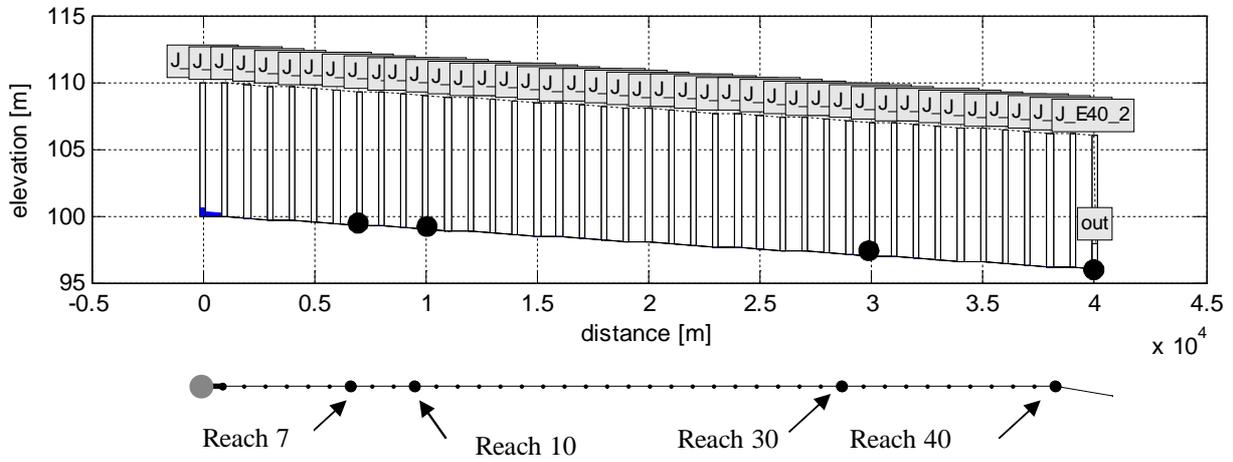


Figure 3.4 Schematic of the hypothetical river modelled in SIMBA by SWMM

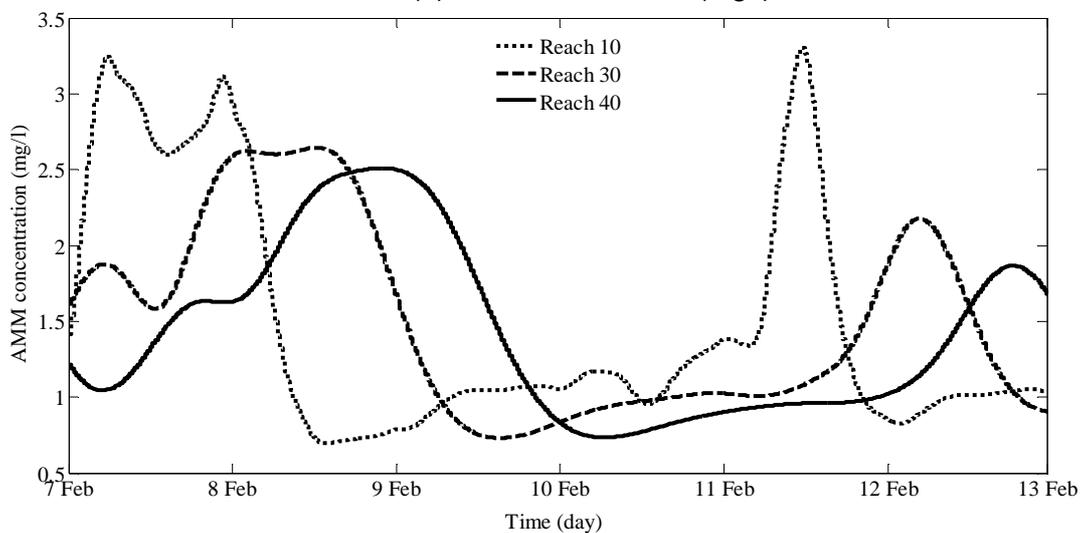
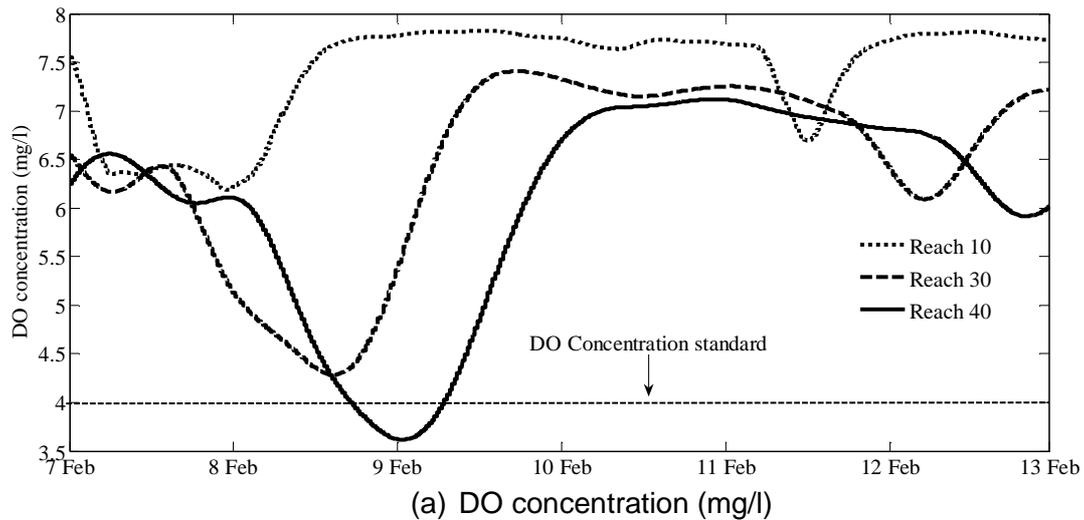


Figure 3.5 DO and AMM concentration in the river under the BC

3.4 Summary

In this chapter the tool used for the simulation modelling of the IUWS was introduced, together with the corresponding methodologies used to model each IUWS component. In addition, the case study used throughout the thesis is introduced, together with the so called Base Case of analysis. Performance of the IUWS was then evaluated for this case in terms of the recipient's water quality indicators (DO and AMM concentrations). The results obtained for the BC clearly demonstrate that:

- The AMM concentration at reach 10 of the river (the critical reach for the AMM concentration) does not violate the standard (4 mg/l) under the base rainfall. Therefore, the existing operational control strategy can

cope with the base rainfall in terms of meeting the AMM concentration standard in the river.

- The DO concentration violates the standard at reach 40 (the critical reach for the DO concentration) under the base rainfall. Therefore, the existing operational control strategy cannot cope with the base rainfall in terms of meeting the DO concentration standard in the river.

Therefore, even under the base rainfall, the analysed IUWS is failing to meet the DO standard in the river. It is expected that things can only worsen (in terms of DO but also AMM) under the assumed climate and/or urbanisation change, i.e. it is unlikely that the current BC operational control strategy will be able to deal with these changes. In Chapter 4, the future climate change and urbanisation growth indicators are introduced. A series of Sensitivity Analyses is then applied to identify the most effective parameters for the operational control of the IUWS.

CHAPTER 4

URBANISATION AND CLIMATE CHANGE IMPACTS

4.1 Introduction

Climate change and urbanisation are among the key factors affecting the future of water quality and quantity in urbanised catchments (Wilby, *et al.*, 2006a) and the ones associated with most uncertainty. In order to respond to these future challenges, it is vital to understand the impact of these factors on urban river water quality, including associated uncertainties and how the wastewater system can best respond and adjust to maintain its performance in changed conditions.

The aim of this chapter is to investigate the impact of climate change and urbanisation on the IUWS performance measured in terms of the receiving water quality (DO and AMM concentrations in the river). The identified significant climate change and urbanisation parameters are then used in Chapter 5 to form a number of scenarios of possible future change with the aim to identify key parameters that could be potentially used to mitigate the negative impact of climate change and/or urbanisation.

The above analyses are performed by using a number of Sensitivity Analysis type methods. These techniques can be broadly classified into local and global methods (Saltelli, *et al.*, 2006). In section 4.2 the applied sensitivity analysis methods are presented in detail. In section 4.3 a correlation analysis (Saltelli, *et al.*, 2000) is performed to analyse the sensitivity of river DO and AMM concentrations to the IUWS model input parameters. In section 4.4 the analysed IUWS model input parameters and the water quality indicators are introduced. In section 4.5 the results of the Local Sensitivity Analysis (section 4.5.1), Global

Sensitivity Analysis (section 4.5.2) and the correlation analysis (section 4.5.3) are presented and discussed. Finally the empirical Cumulative Distribution Function (CDF) of each water quality indicator is derived to evaluate the risk of failures under the influence of each climate change parameter.

4.2 Sensitivity Analysis Methods

Saltelli *et al.* (2006) classified the Sensitivity Analysis methods into two broad approaches: (1) Local Sensitivity Analysis (LSA) methods and (2) Global Sensitivity Analysis (GSA) methods. A range of these methods are used here to identify significant climate change, urbanisation and IUWS operational control parameters. This was necessary because a relatively large number of these parameters are considered in this study which makes the sensitivity analysis more demanding. A hierarchical approach is adopted where the LSA method is used for initial screening, i.e. identification and removal of insignificant input parameters. The GSA methods are then applied to the remaining input parameters to identify the significant ones by considering the interactions between the analysed parameters.

4.2.1 Local Sensitivity Analysis Method

In a local analysis, one parameter at a time is perturbed while the others are fixed at their nominal (i.e. default) values.

In this study, the BC represents the current situation in the IUWS, i.e. without any consideration of climate change and urbanisation effects. The analysed IUWS input parameters (see Table 4.1) are all set to their default values in the BC, as defined by Schütze *et al.* (2002a).

The Tornado type graphs are used to visualise the LSA results, where the relative differences between the analysed IUWS model outputs in the BC and from the LSA (i.e. LSA outputs) are arranged vertically in order of descending sensitivity (Deb, 2001). This enables visual identification of the most significant input variables. When preparing the Tornado graphs for this study, the following procedure was used:

1. Select one IUWS model input (urbanisation, climate change or system control operation parameter) and change its value from default to upper (i.e. maximum) or lower (i.e. minimum) value in the considered range.

Keep the other input parameter values at their nominal values (see Table 4.1).

2. Run the IUWS model and evaluate the relevant IUWS model outputs (AMM and DO concentrations in the river).
3. Calculate the relative difference (percent change) for the analysed IUWS model outputs relative to the BC.
4. Rank the obtained relative differences in a descending order and identify the most sensitive IUWS model input parameters.

Note that Tornado graphs obtained include both negative and positive values. The positive values represent the output variables value that have increased value relative to the BC and the negative ones represent decreasing values (Saltelli, *et al.*, 2000).

4.2.2 Global Sensitivity Analysis Method

In GSA, the analysed IUWS model input parameters are varied simultaneously and the effects of their possible interactions are therefore taken into account. Therefore, unlike the LSA methods, the GSA methods take into account both local and global effects of input parameters on the analysed IUWS model outputs. The RSA technique (Hornberger & Spear, 1981) has been used here because of its capability to perform the GSA for highly-dimensional and non-linear models, such as the IUWS model used here (Fu, *et al.*, 2009).

4.2.2.1 Regional Sensitivity Analysis Method

The main idea behind the RSA is a division of the model output space into behavioural (B) or non-behavioural (NB) regions in terms of *a priori* defined criterion. The IUWS output variable belongs to the behavioural group of outputs if it meets the pre-defined criterion and vice versa.

The RSA procedure has the following principal steps:

1. Identify the most important sources of uncertainty in the IUWS model input parameters using the LSA method described in section 4.2.1;
2. Characterise the uncertainties of identified parameters by assigning some probability distribution function (PDF) to each IUWS model input parameter. The uniform PDF is used here as the analysed IUWS model input parameters are not precisely known and there is no data available

- to estimate the actual PDF function. Having said this, the RSA performed is generic, i.e. any other PDF (or combination of PDFs) can be used;
3. Generate multiple input parameter sets by using a sampling technique. The LHS method (see next section), capable of stratified sampling, is used in this study to improve the sampling efficiency and thus reduce the number of samples required to obtain reliable results;
 4. Run the IUWS model to evaluate the corresponding model outputs for each sample considered. Classify each input parameter set either as a 'behavioural' or 'non-behavioural', based on the *a priori* defined criterion. For a multi-objective analysis, this classification is conducted for each output separately;
 5. For behavioural and non-behavioural groups of samples, assign each of the parameter sets likelihood estimated from its relevant output value. The cumulative marginal distribution of behavioural and non-behavioural parameter sets is then derived for each output. Figure 4.1 shows a schematic of the cumulative marginal distribution of behavioural and non-behavioural parameter sets.

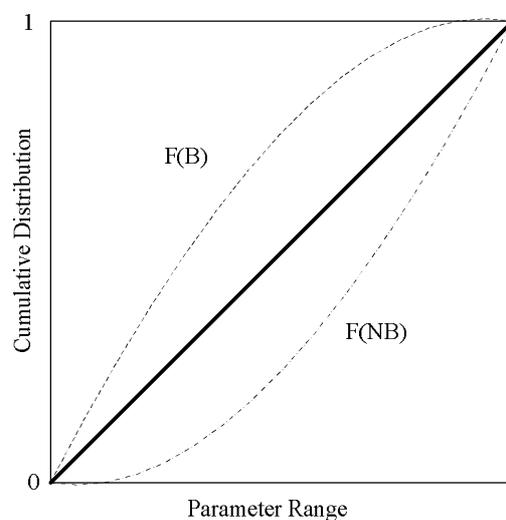


Figure 4.1 Schematic of the cumulative marginal distribution B and NB in the RSA method

The difference between the two cumulative marginal distributions can be estimated by using a two-sample Kolmogorov-Smirnov (KS) test (Chakravarti & Roy, 1967). The statistic $D_{m,n}$ is determined as the maximum vertical distance between the cumulative distribution of behavioural and non-behavioural curves as follows:

$$D_{m,n} = \sup |S_B(x) - S_{NB}(x)| \quad (4.1)$$

where S_B and S_{NB} are the empirical distribution functions for n behavioural and m non-behavioural samples, respectively. The statistic is sensitive not only to differences in central tendency but also to any difference in the distribution functions. Accordingly, the significance of the statistic indicates the importance of the relevant parameter in terms of the specific IUWS model output. Thus, the larger the value of $D_{m,n}$, the more important the input parameter analysed. RSA has been widely applied in the fields of environmental and hydrological modelling (Cox & Whitehead, 2005; McIntyre, *et al.*, 2003b), and provides a theoretical foundation for the development of the generalised likelihood uncertainty estimation method (Beven & Binley, 1992).

4.2.2.2 Latin Hypercube Sampling Method

LHS is designed to accurately recreate a distribution through fewer samples compared with pure random sampling. This technique is a special method under the umbrella of stratified sampling which selects random samples of each random variable over its range in a stratified manner. Tung & Yen (2005) summarised this method as the following steps:

Consider a multiple integral involving K random parameter values:

$$G = \int_{x \in X} g(x) f_x(x) dx = E[g(x)] \quad (4.2)$$

where, $X = (X_1, X_2, \dots, X_k)^t$ is K dimensional vector of random parameter values; $g(x)$ is the given function of outputs and $f_x(x)$ is their joint PDF. The LHS technique divides the plausible range of each random parameter values into M ($M \geq K$ in practice) equal-probability intervals. Within each interval, a single random parameter values is generated resulting in M random parameter values for each random variable. The expected value of $g(x)$, then, is estimated as equation (4.3).

$$\hat{G} = \frac{1}{M} \sum_{m=1}^M g(X_{1m}, X_{2m}, \dots, X_{km}) \quad (4.3)$$

where, X_{km} is the parameter value generated for the K^{th} random parameter value X_k in the m^{th} set.

The principal LHS method steps are as follows:

1. Select M subintervals for each random parameter values and divides the plausible range into M equal-probability intervals according to equation (4.4).

$$F_k(x_{km}) = \int_{x_k}^{x_{km}} f_k(x_k) dx_k = \frac{m}{M} \quad (4.4)$$

where, $F_k(\cdot)$ is the CDF of the random parameter value X_k .

2. Generate M standard uniform random parameter values from $U(0, 1/M)$
3. Determine a sequence of probability values p_{km} , for $k=1, 2, \dots, K$; $m=1, 2, \dots, M$ using equation (4.5).

$$P_{km} = \frac{m-1}{M} + \varphi_{km} \quad (4.5)$$

in which $\{\varphi_{k1}, \varphi_{k2}, \dots, \varphi_{km}\}$ are independent uniform random numbers from $U(0, 1/M)$.

4. Generate random parameter values for each of the random parameter values using equation (4.6).

$$x_{km} = F_k^{-1}(P_{km}) \quad (4.6)$$

5. Randomly permutate generated random sequences for all random parameter values.
6. Estimate G by using equation (4.3).

Using the LHS technique, the usual estimators of G and its distribution function are unbiased (McKay, 1988).

4.3 Correlation Analysis

Correlation analysis is performed to evaluate the level of correlation between pairs of IUWS model input and output variables. If highly correlated, the resulting predictive relationship between two analysed variables can additionally confirm the insights gained from the sensitivity analysis regarding the most significant input parameters. In line with this, in this study, scatter plots of the most significant input parameters (obtained by the LSA and GSA) in terms of the model outputs are provided to show visually the correlation between them. Scatter plots can be considered as global measures of correlation and are

model independent (Helton, 1993). In addition, the Pearson correlation coefficient R^2 is used to represent the strength of the linear relationship between two variables (Saltelli, *et al.*, 2000).

4.4 IUWS Model Input Parameters and Outputs

4.4.1 Input Parameters

The three groups of IUWS model input parameters investigated here are the climate change parameters, urbanisation parameters and system operational control parameters.

4.4.1.1 Climate Change Parameters

The rainfall has been selected as the indicator of climate change in this work considering its important impact on the IUWS operation and design. Hulme *et al.* (2002) and IPCC (2000) estimated the future pattern changes in rainfall for the UK indicating a future with wetter winters and drier summers for some regions under certain climate change scenarios. With regard to the work done here, the Medium-High IPCC emissions scenario has a good match with the case study considered here as this case study is located in the Southeast of England.

According to the above two reports, an increase in rainfall depth and/or intensity is possible under the future climate. Having said this, rather than undertake a detailed regional climate model study, based on full scenario analysis, a simplified approach has been adopted here. In this approach, the rainfall increase (in both depth and intensity) is represented using the following simplified approach:

- **RD:** This parameter represents the percentage increase in Rainfall Depth. This increase under climate change is achieved by applying a fixed percentage value to base case rainfall intensities across the entire event/time-series. As a consequence, the total rainfall depth increased.
- **RI:** This parameter represents the percentage increase in Rainfall Intensity. This increase under climate change is achieved by applying a fixed percentage value to rainfall intensities across the entire event/time-series whilst maintaining the same cumulative rainfall depth as follows:

$$y_t = \max(0, \bar{x} + (x_t - \bar{x} \times w) \times d) \quad (4.7)$$

Where, y_t is the new value of rainfall intensity (i.e. following assumed climate change) at time t , x_t is the value of rainfall intensity at time t in the base rainfall series (i.e. without any climate change), \bar{x} is the average of rainfall intensity in the base rainfall, d is a scaling factor and w is a weighting factor that acts as the adjustor of \bar{x} . As shown in equation (4.7), the values of y_t have a minimum value of zero to avoid generating negative rainfall rates which can result from the total rainfall depth increases. To generate a new rainfall series, an initial value is assigned to the factor w , and the new rainfall series are calculated using equation (4.7). Then the total rainfall depth of the new series is computed and compared with the base rainfall depth value. If the two depth values are not equal the factor w is used to adjust the difference by trial and error. This process is repeated until the two series have the same rainfall depth. The percentage increase values (RD and RI) considered in this chapter are given in Table 4.1.

4.4.1.2 Urbanisation Parameters

Urbanisation can, in principle, be represented by a number of different parameters. The following IUWS model input parameters are used in this study:

- **POP:** In this study POP represents the percentage increase in population count over a given period of time and is, obviously, related to the DWF quantity, but may also influence DWF quality (Butler & Davies, 2011; Fu, *et al.*, 2009). Population growth has also been shown to be related to other urbanisation indices such as housing density and occupancy (Environment Agency, 2007; Jefferies, 2005; Office for National Statistics (ONS), 2010). In the UK, population growth by 2030 is predicted at 4.5% as a minimum and 15% as a maximum (Department for Communities and Local Government, 2010). In this study, a range of POP values has been considered as shown in Table 4.1.
- **PCW:** PCW is defined as Per Capita Water Consumption in litre/day/person. This factor has a key role in influencing domestic wastewater quantities. As Butler & Davies (2011) indicate, approximately 95% of the water consumed is returned to the sewer system as wastewater. PCW itself can be influenced by a number of factors including

changing household demographic composition, the changing structure of the UK economy, developing environmental technologies and water charging policies (Environment Agency, 2007). Rather than considering all these parameters separately, the future urbanisation impact is modelled here in a cumulative fashion, via single parameter (PCW).

- **IMP:** IMP represents the percentage of impervious surfaces increase which has a direct influence on the rate of stormwater runoff in urban areas (Butler & Davies, 2011). The growth of impervious surfaces, by definition, represents a change from natural catchment surfaces due to development in urban areas. This rate of increase of imperviousness, in a given urban area is defined as *urban creep*, and has increased significantly over recent years in many urban areas in the UK (UKWIR, 2010). The UK government policy is currently in a period of considerable change (Department for Communities and Local Government, 2010), thus making accurate predictions of future urban creep and hence imperviousness difficult. However, some data is available (CIWEM, 2009) and the range shown in Table 4.1 is used for the analysis in this thesis.
- **NH₄⁺:** NH₄⁺ is defined as the concentration of Ammonium (NH₄⁺) in DWF and has been considered as an urbanisation parameter in this study. This is a rather different parameter to the previous ones in that it assumes the possible roll-out of urine separation toilets. This is unlikely in the UK in the short-term, but is a possible long-term option. Urine separation toilets reduce both the hydraulic and nutrient loads in the sewer systems. Achleitner *et al.* (2007b) and Semadeni-Davies *et al.* (2008) estimated that urine separation in new homes could reduce the specific load of nitrogen by some 25%. This has been used as a basis for the range considered in Table 4.1.

4.4.1.3 Operational Control Parameters

In addition to the aforementioned IUWS model input parameters which are used to represent the potential impact of climate change and urbanisation, a number of IUWS operational control parameters are also analysed to identify the best candidates for mitigating negative effects of climate change and/or urbanisation. The following IUWS operational control parameters are analysed here:

- **Q_{maxout}**: This parameter is the maximum outflow rate from the storage tank in the sewer system. This operational control parameter controls CSO discharges to the river and the wastewater inflow to the wastewater treatment plant.
- **Q_{maxin}**: This parameter 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 parameter 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.
- **Q_{empst}**: The filling of the storm tank is controlled by the maximum inflow rate to the primary clarifiers. The tank is emptied at a certain pump rate, as soon as the inflow rate to the plant drops below a pre-specified threshold value.
- **Q_{RAS}**: The return activated sludge is taken from the secondary clarifiers and is pumped back to the head of the aerator. Also there is a waste sludge rate which is set to a constant value of 660 m³/d.

The nominal values of the above parameters and the ranges of values used in different sensitivity analyses are given in Table 4.1.

4.4.2 IUWS Model Outputs

With regard to the aim of this chapter to perform a water quality-based evaluation of the IUWS performance, several potential water quality indicators can be addressed. These potential parameters are COD, nitrate, ammonia, phosphorus, sulphur, hydrocarbons, heavy metals, micro-organisms etc. Selection of proper parameter(s) for the system evaluation depends on the problem in hand and the aim of the water quality analysis. As the case study introduced and used here has a nitrogen removal-based WWTP and also with regard to the pure hypothetical river considered in this study, it was assumed the following two indicators have the most significant impact on the recipient water quality.

Additionally Milne *et al.* (1992) formulated the fundamental intermittent standards for water quality factors for aquatic life in rivers. These standards are expressed in terms of concentration of these quality indicators. Such criteria for England and Wales are set out in the rivers ecosystem classification (DoE, 1994; FWR, 1998) and include several water quality parameters such as BOD, DO, total ammonia, un-ionised ammonia etc. Two important water quality parameters were selected as IUWS model outputs in this study as follows:

- **DO:** DO represents the DO concentration in the river. The concentration of DO is an excellent indicator of the 'health' of receiving water. Because of its importance for aquatic life, DO is one of several water quality parameters which traditionally has received most attention and consequently it was considered in this study as an indicator of the health of aquatic life too. The processes affecting the DO concentration in a river include reaeration, decomposition, sediment oxygen demand, photosynthesis, algal respiration and nitrification. A critical threshold is considered on the basis of the Urban Pollution Management (UPM) manual (FWR, 1998). If DO drops below the critical threshold the aquatic life is in danger and the system operation must be set to avoid exceedances. Based on the UPM standard values, we assume a 4 mg/l constraint for DO concentration.
- **AMM:** AMM represents the Ammonium concentration in the river. Ammonium is a constituent part of DWF, partly removed by nitrifying wastewater treatment works (assuming $\text{pH} \leq 7$). This product consumes the DO during degradation processes and therefore affects the concentration of DO and consequently the aquatic life in the rivers. Therefore similar to DO concentration AMM concentration is an important indicator of receiving water health. Alike to DO, a 4 mg/l constraint (based on the UPM standard for AMM concentration) is assumed for AMM in this case study for protection of aquatic life given in UPM manual (FWR, 1998). Therefore when Ammonium concentration exceeds the 4 mg/l critical threshold, the aquatic life is considered to be in danger and the system operation needs to be improved.

4.5 Case Study

4.5.1 Introduction

The above sensitivity analyses have been applied to the case study introduced in Chapter 3 with the aim to investigate the impact of climate change and urbanisation on the IUWS performance. The following sections summarise the input parameter values considered and the corresponding results obtained.

4.5.2 Input Parameter Values Used in Sensitivity Analyses

As mentioned in section 4.4.1.1, increases in the climate change parameters are considered (RD, RI). Hulme *et al.* (2002) showed a 30 percent increase in 2080 for winter rainfall in the UK under the Medium-High IPCC scenario. In addition to a 30 percent increase in rainfall, 10 and 20 percent are also applied to the base rainfall intensity to increase the total rainfall depth with the same duration as the base rainfall. Furthermore, the assumed 10 percent and 20 percent increase here, have the potential to cover the mentioned time horizons difference between climate change and urbanisation parameters. Based on the studies by Hulme *et al.* (2002) and Osborn *et al.* (2000), and similar to RD, three cases of 10, 20 and 30 percent increases to the base rainfall intensities are assumed.

The climate change parameters illustrated in section 4.4.1.1 are presented in Table 4.1. Also with regard to the operational control parameters described in section 4.4.1.3, the possible ranges of them are observed in Table 4.1. The possible range of the considered urbanisation parameters described in section 4.4.1.2 is set according to Defra (2006) and Fu *et al.* (2009) and is shown in Table 4.1.

Table 4.1 Climate change, urbanisation and operational control parameters' nominal values and their value ranges

Parameter	Unit	Nominal value	Value/Range
RD	%	0	[10, 20, 30]
RI	%	0	[10, 20, 30]
POP	%	0	[4.5, 15]
IMP	%	0	[5, 15]
PCW	litre/person/day	180	[80, 260]
NH ₄ ⁺	mg/l	27.7	[20, 30]
Q _{maxout}	m ³ /d	5× DWF*	[3×DWF*, 8×DWF*]
Q _{maxin}	m ³ /d	3× DWF*	[2×DWF*, 5×DWF*]
Q _{trigst}	m ³ /d	24192	[16416, 31104]
Q _{empst}	m ³ /d	12096	[6912, 24192]
Q _{RAS}	m ³ /d	14688	[6912, 24192]

*The DWF considered here is the DWF of the BC (27,500 m³/d)

4.5.3 LSA Results and Discussion

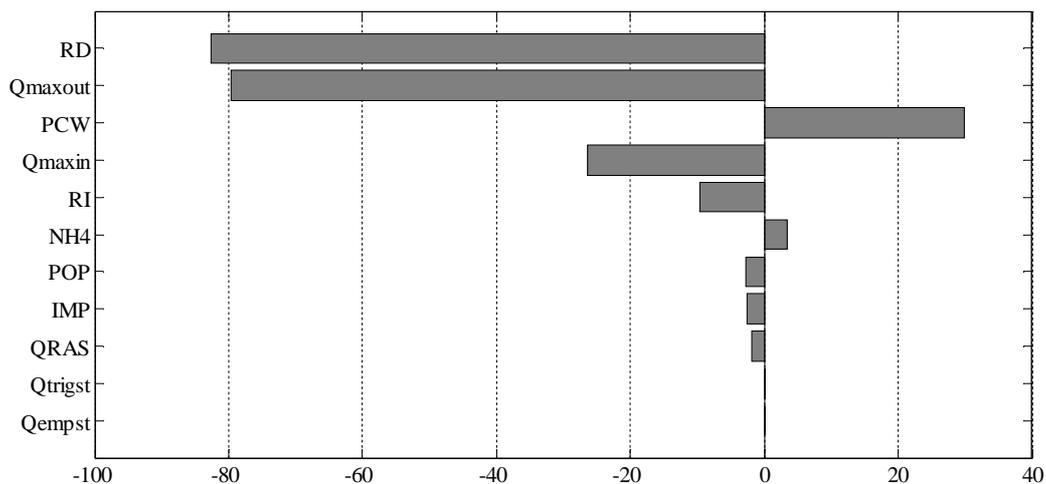
The cases considered in the LSA done here include four urbanisation parameters (PCW, POP, IMP and NH₄⁺), two climate change parameters (RD and RI) and five IUWS operational control parameters (Q_{maxout}, Q_{maxin}, Q_{trigst}, Q_{empst}, Q_{RAS}). Note that in the LSA, all the input parameters analysed are initially set to their nominal values. The input parameters are then varied, one at a time by using the alternative values shown in Table 4.1. In addition, the two rainfall-based climate change parameters are varied as already explained in section 4.4.1.1. The Tornado graphs shown in Figure 4.2 and Figure 4.3 present the LSA results obtained by using the methodology outlined in section 4.2.1.

Figure 4.2a and Figure 4.2b demonstrate the sensitivity of DO to the analysed IUWS model inputs and Figure 4.3a and Figure 4.3b demonstrate the corresponding results for the AMM case. The following can be noted from these figures:

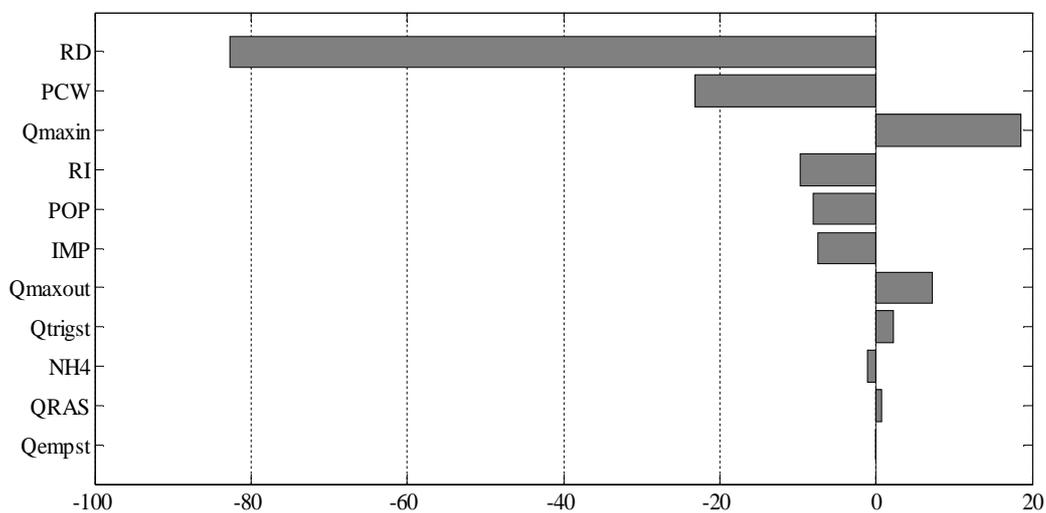
- The most significant climate change parameter is RD. Figure 4.2a and Figure 4.2b indicate only the 30 percent increase in rainfall depth results in a more severe deterioration of DO than urbanisation and this is more influential than any change to system operation. Also the 30% increase in RD has a significant impact on deterioration of AMM in the river (see Figure 4.3a and Figure 4.3b). This deterioration is a consequence of

increasing the CSOs and storm tank overflows which is a consequence of excess rainfall volume. Note that RD has significantly larger impact on DO and AMM deterioration than RI. Finally, note that the LSA results for 10% and 20% increase, have not been included in the Tornado graphs shown in Figure 4.2 and Figure 4.3 as their relative impact on the DO and AMM values is less significant than in the 30% case (and this, in turn, makes these figures more readable).

- PCW has the most significant impact on river water quality of all urbanisation parameters analysed. The minimum value of PCW improves the DO and AMM (see Figure 4.2a and Figure 4.3a) while the opposite happens when PCW is set to the maximum value (see Figure 4.2b and Figure 4.3b).
- As shown in Figure 4.2 and Figure 4.3, Q_{maxout} and Q_{maxin} are the two most significant operational control parameters with the highest impact on river water quality. The reason is that these two parameters directly control the CSOs and storm tank overflow discharges which, in turn, affect the quality of water in the river (Butler & Davies, 2011). In addition, Q_{trigst} also has a significant impact on AMM in the river as it controls storm tank overflows (see Figure 4.3a).

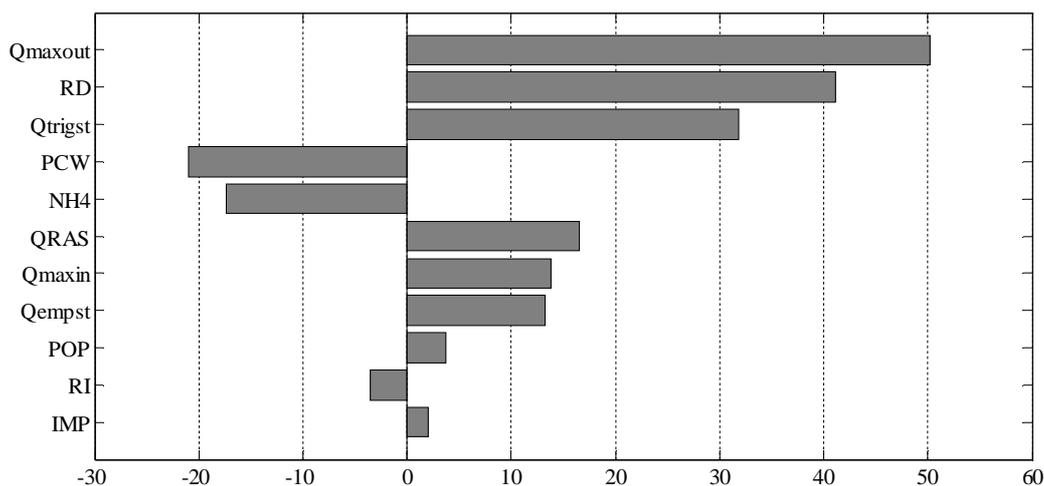


(a) Relative variation of DO concentration to the BC for minimum values of the IUWS model input parameters (%)

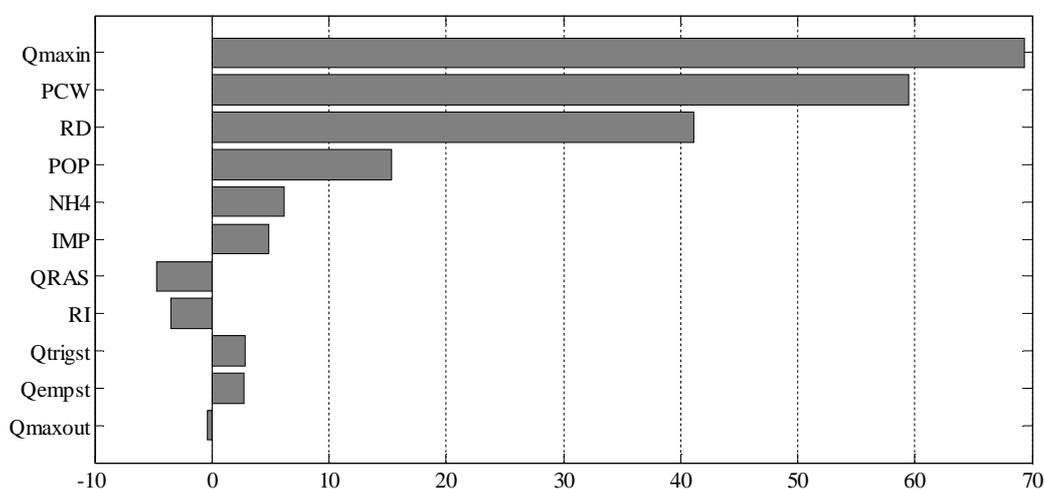


(b) Relative variation of DO concentration to the BC for maximum values of the IUWS model input parameters (%)

Figure 4.2 The LSA results to DO concentration



(a) Relative variation of AMM concentration to the BC for minimum values of the IUWS model input parameters (%)



(b) Relative variation of AMM concentration to the BC for maximum values of the IUWS model input parameters (%)

Figure 4.3 The LSA results to AMM concentration

Based on the LSA rankings obtained (see Figure 4.2 and Figure 4.3), the following significant parameters are selected for further investigation using GSA:

- RD and RI are selected to represent climate change,
- PCW, POP and IMP to represent urbanisation, and
- Q_{\maxout} , Q_{\maxin} and Q_{trigst} to represent IUWS operational control parameters.

4.5.4 GSA Results and Discussion

4.5.4.1 General

The GSA is performed here using the RSA method discussed earlier with random Latin Hypercube samples generated in the defined ranges of urbanisation parameters and system operational control parameters (see Table 4.1). These parameter sets are then combined with three rainfall series to evaluate the receiving water quality, respectively, that is, the original rainfall series and two rainfall series generated in the case of 30 percent increase in rainfall depth (i.e. RD) and in rainfall intensity (i.e. RI). RD is considered as it is one of the most sensitive parameters. Although RI did not show such a great impact on the quality of water as RD, it is investigated further in the GSA for possible interactions with this and other parameters.

All input parameter sets generated were divided into two groups, behavioural and non-behavioural, on the basis of the pre-defined threshold value of 4 mg/l for both IUWS model outputs considered (FWR, 1998). The behavioural group has a DO concentration above 4 mg/l and the AMM concentration below 4 mg/l (see section 4.5.4.1).

The CDFs of both the behavioural and non-behavioural groups were plotted with regard to water quality indicators. The difference between the two cumulative marginal distributions represents the parameter's sensitivities and can be estimated by a two-sample KS test. The KS statistics obtained under the climate change parameters are shown in Table 4.2 for both IUWS model outputs and will be analysed in the following section (4.5.4.2).

4.5.4.2 GSA to the Urbanisation Parameters

This section presents and discusses the results of GSA with focus on investigating the sensitivity of DO and AMM to selected urbanisation parameters by LSA (see section 4.5.3) under climate change parameters (RD and RI). Theoretically, the diagonal line (D-line) indicates the parameter has a uniform distribution and the IUWS model is not sensitive to this parameter in terms of the chosen likelihood measures. Any distance from the D-line shows a non-uniform distribution and the model is sensitive to this parameter.

Based on Figure 4.4, the following observations can be made for the considered urbanisation parameters:

- In general, departures of the urbanisation parameters from the D-line under RD are more significant than under RI. In other words the sensitivity of the water quality indicators to the urbanisation parameters under RD is more significant than under RI.
- The most significant departures from the D-line are observed for PCW (see Figure 4.4.5, Figure 4.4.6, Figure 4.4.11 and Figure 4.4.12). With changing the climate (specifically under RD as shown in Figure 4.4.5, Figure 4.4.11), PCW values satisfying water quality standards (as KS statistics in Table 4.2), are almost in the lower bound of the considered PCW range. In other words reducing PCW is important for meeting the water quality standards (especially regarding DO concentration in the river) under climate change scenarios.
- Figure 4.4.1, Figure 4.4.2, Figure 4.4.7 and Figure 4.4.8 show that DO is considerably more sensitive than AMM to IMP and this sensitivity is more significant under RD. The excess volume of rainfall under RD causes more runoff and this runoff intensifies when the imperviousness increases. Increasing the runoff causes CSOs and storm tank overflows and consequently deterioration of DO concentration in the river. Therefore under a changing climate, more attention should be paid to controlling imperviousness (urban creep), although this is of lesser importance than the PCW.

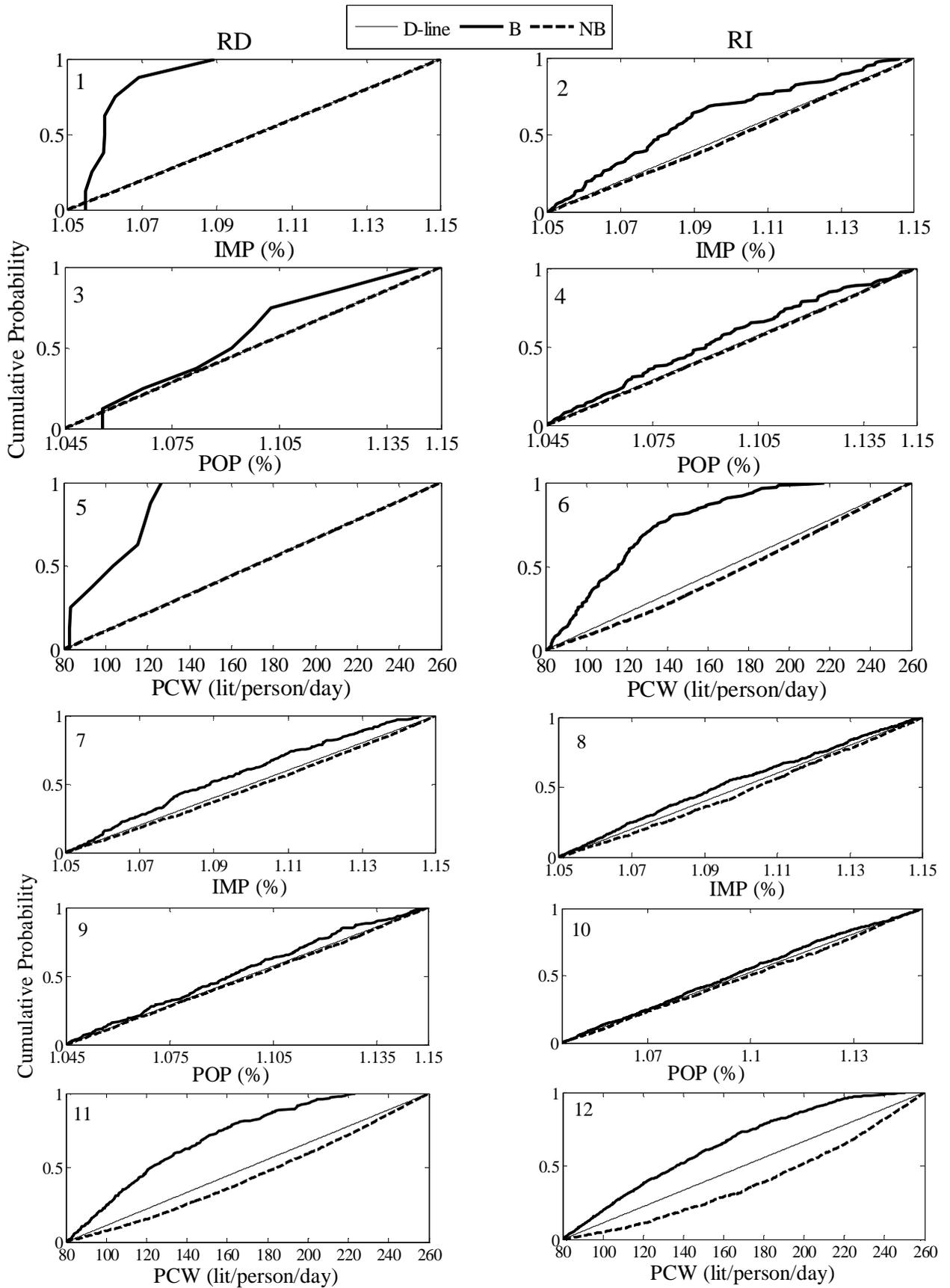


Figure 4.4 CDFs of the selected urbanisation parameters from GSA under two climate change parameters with regard to DO (Figure 4.4.1 to Figure 4.4.6) and AMM (Figure 4.4.7 to Figure 4.4.12) in the river, respectively.

Table 4.2 KS statistic of each input parameter for the model outputs

	Model outputs	DO		AMM	
	climate change parameters	RD	RI	RD	RI
Urbanisation parameters	IMP	0.68	0.27	0.16	0.12
	POP	0.20	0.11	0.11	0.07
	PCW	0.76	0.50	0.41	0.40
Operational control parameters	$Q_{\max\text{out}}$	0.93	0.64	0.59	0.56
	$Q_{\max\text{in}}$	0.29	0.26	0.13	0.20
	Q_{trigst}	0.28	0.07	0.13	0.10

4.5.4.3 GSA to the Operational Control Parameters

This section presents and discusses the results of GSA with focus on investigating the sensitivity of DO and AMM to selected operational control parameters by LSA method (see section 4.5.3) under climate change parameters (RD and RI). The following observations can be made based on the results obtained:

- The departures from the D-line in Figure 4.5.1 and Figure 4.5.2 show that $Q_{\max\text{out}}$ has the most significant impact on DO. Figure 4.5.1 and Figure 4.5.2 indicate that the DO is more sensitive than AMM to $Q_{\max\text{out}}$ as shown in Figure 4.5.7 and Figure 4.5.8. Also, as can be observed from these figures, nearly maximum departures (shown by line) are observed near the maximum value of $Q_{\max\text{out}}$ in the case of RD. An increased $Q_{\max\text{out}}$ reduces the volume of CSO discharges in the river, thus helping maintain the water quality under climate change. The sensitivity of $Q_{\max\text{out}}$ to the RD is larger than the corresponding sensitivity to the RI.
- In addition to $Q_{\max\text{out}}$, DO is also sensitive to $Q_{\max\text{in}}$, as shown in Figure 4.5.3 and Figure 4.5.4 but the sensitivity to $Q_{\max\text{in}}$ is less than $Q_{\max\text{out}}$. These figures show that most of the departures (shown by line) happen near the upper values of $Q_{\max\text{in}}$ under the climate change parameters. This happens because decreasing the $Q_{\max\text{in}}$ increases the storm tank overflows. The two aforementioned figures also show that for both climate

change parameters, the sensitivity of DO to Q_{\max} does not have a marked difference.

- The sensitivity of DO to Q_{trigst} is observed only in the case of RD as shown in Figure 4.5.5. The maximum departure from the D-line is associated with the lowest value of Q_{trigst} . This indicates that for maintaining the DO quality criteria in the river, the operational control scheme reduces the storm tank overflows. Figure 4.5.6 shows that, under the RI, AMM is not sensitive to Q_{trigst} .

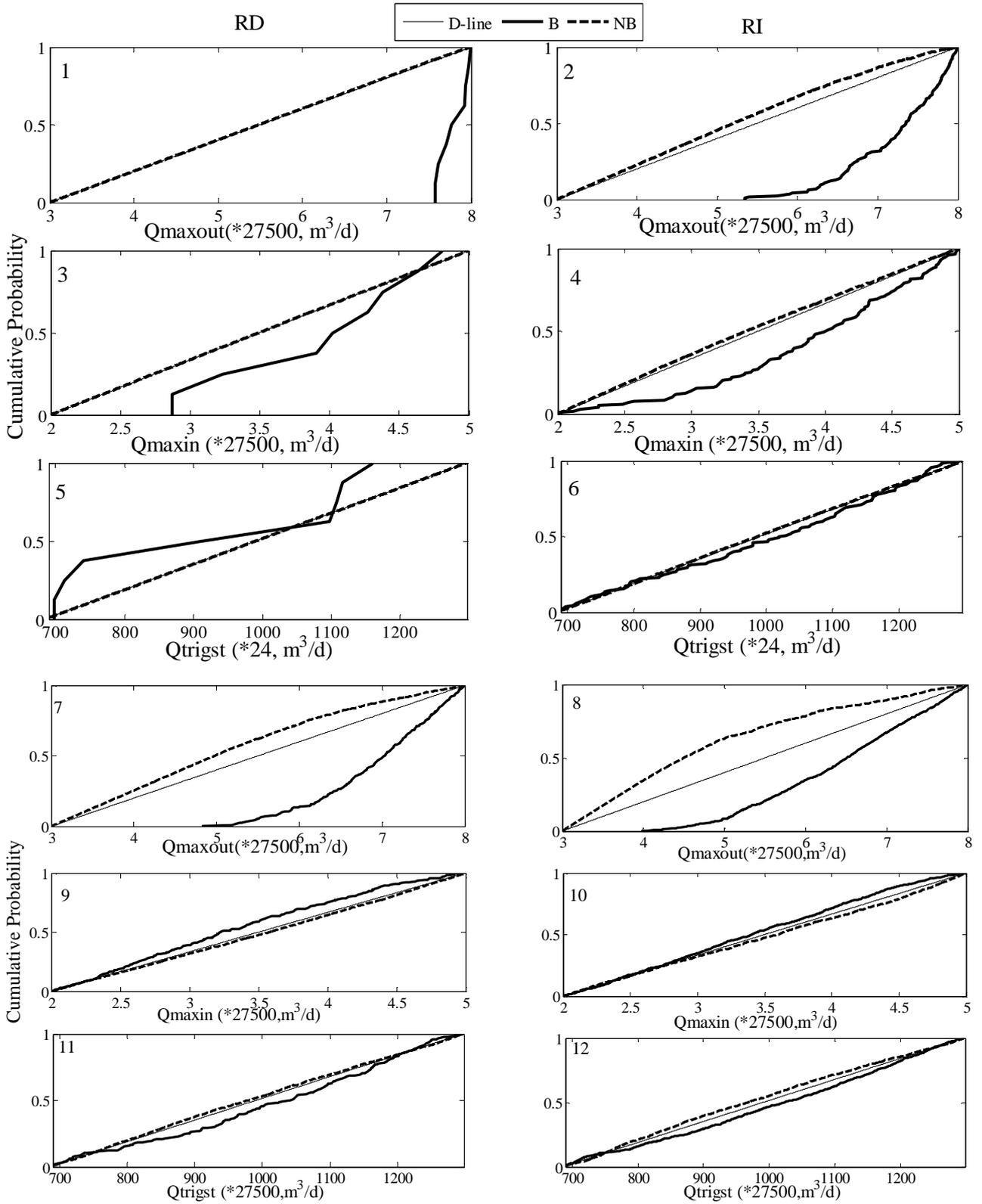


Figure 4.5 CDFs of the selected operational control parameters from GSA under two climate change parameters with regard to DO (Figure 4.5.1 to Figure 4.5.6) and AMM (Figure 4.5.7 to Figure 4.5.12) in the river.

4.5.5 Correlation Analysis Results and Discussion

Although the KS statistic provides an insight into the distinction between behavioural and non-behavioural parameters, it may not identify the regional sensitivity hidden by high correlation between parameters. Therefore the results of the RSA need to be interpreted in conjunction with the parameter covariance or correlation matrix (McIntyre, *et al.*, 2003a). As the sensitivity results showed, PCW and Q_{maxout} are the two most important parameters.

Table 4.3 shows the correlation coefficients for PCW and Q_{maxout} . As it can be seen from this table, the dominating relationship is observed between Q_{maxout} and DO for both RD and RI as both values (0.75 and 0.87 respectively) are relatively large, i.e. closer to one than other values. The positive values obtained indicate that with increasing Q_{maxout} , DO is improved, by controlling CSOs via Q_{maxout} .

Figure 4.6a and Figure 4.6b show the relationship between Q_{maxout} and DO under both climate change parameters. The dashed lines show the water quality standards (4 mg/l) for DO and AMM. As it can be observed from these figures, with increasing Q_{maxout} , the numbers of samples which have DO above the standard (dashed line) is reduced by a changing climate and this reduction is further increased under RD. It is also demonstrated that it is difficult to maintain the quality of DO in the river without increasing Q_{maxout} and consequently reducing CSOs. This shows the importance of the role of IUWS operational control (and related operational control parameters) for maintaining the quality of DO in the river.

Table 4.3 Correlations between system input parameters and IUWS model outputs

IUWS model output (Climate Change Parameter)	Q_{maxout}	PCW
DO (under RD)	0.75	0.017
DO (under RI)	0.87	-0.46
AMM (under RD)	-0.18	0.43
AMM (under RI)	-0.15	0.51

Regarding the AMM (see Table 4.3), the maximum correlation coefficients are observed with PCW. In other words, in this study, the correlation between AMM and PCW is more significant than correlation to any of other input parameters under climate change. As can be observed from Figure 4.6c and Figure 4.6d, more non-behavioural samples are observed near the maximum value of PCW for AMM showing that the increase in PCW under climate change has the potential to increase DWF and consequently lead to deterioration of water quality in river.

Figure 4.7 represents the empirical CDF of water quality indicators under climate change based on the generated samples from the LHS method. As it can be observed from Figure 4.7a, the probability of failure (i.e. the probability of the DO concentration rising below the threshold value of 4 mg/l) increases from 49% to 88% and nearly 99% assuming RI and RD respectively. In other words, the climate change parameter RD has a greater negative impact on the DO than RI because of the increased CSO discharges into the river.

The probability of AMM failure in the river (i.e. the probability of the AMM concentration rising above the threshold value of 4 mg/l) also increased with an increasingly worsening climate. The probability of failure increases by 12% for RI and 34% for RD (see Figure 4.7b). The AMM failure is a consequence of the increased CSO discharges i.e. discharges of untreated wastewater into the river under worsening climate conditions.

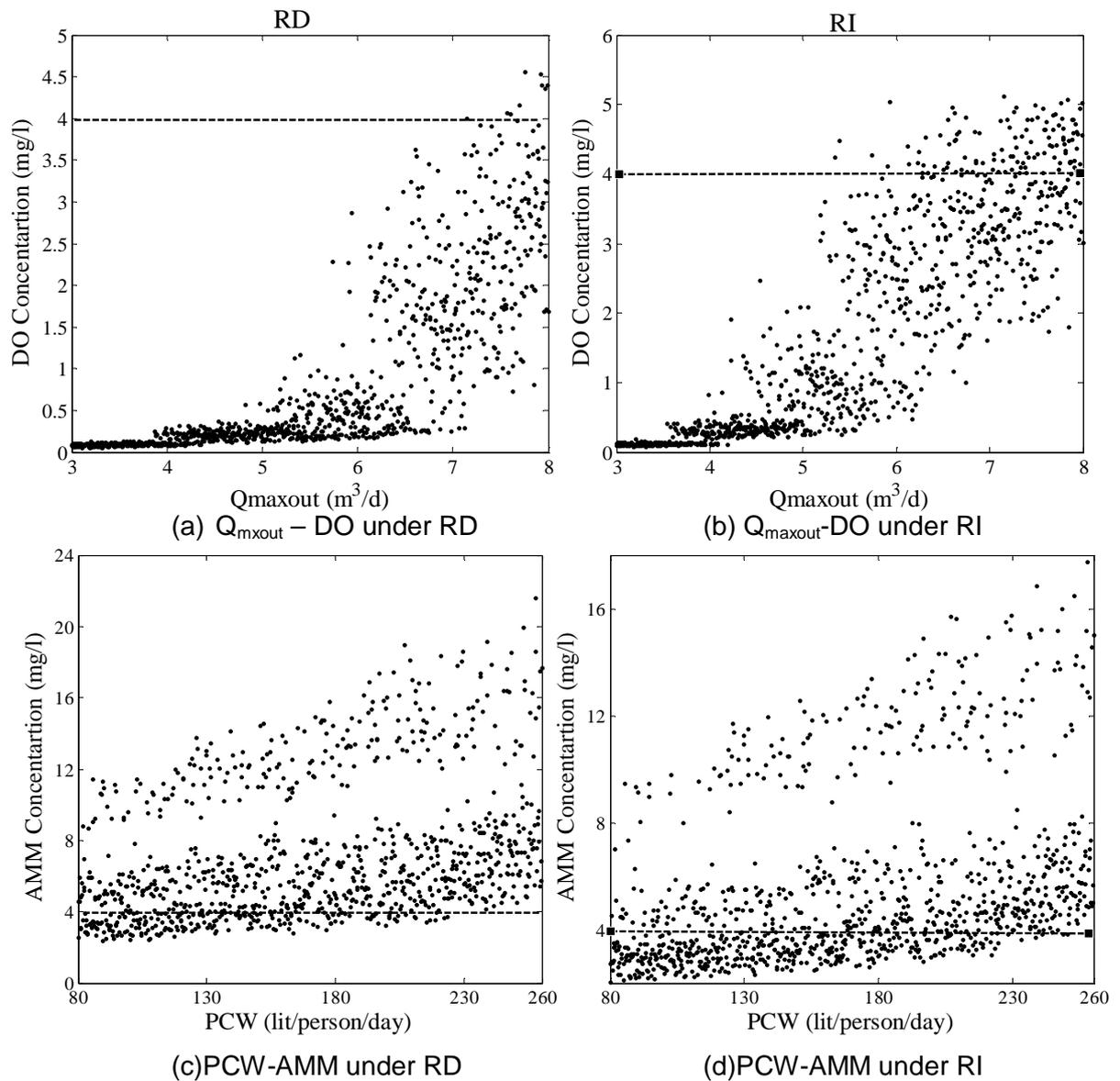
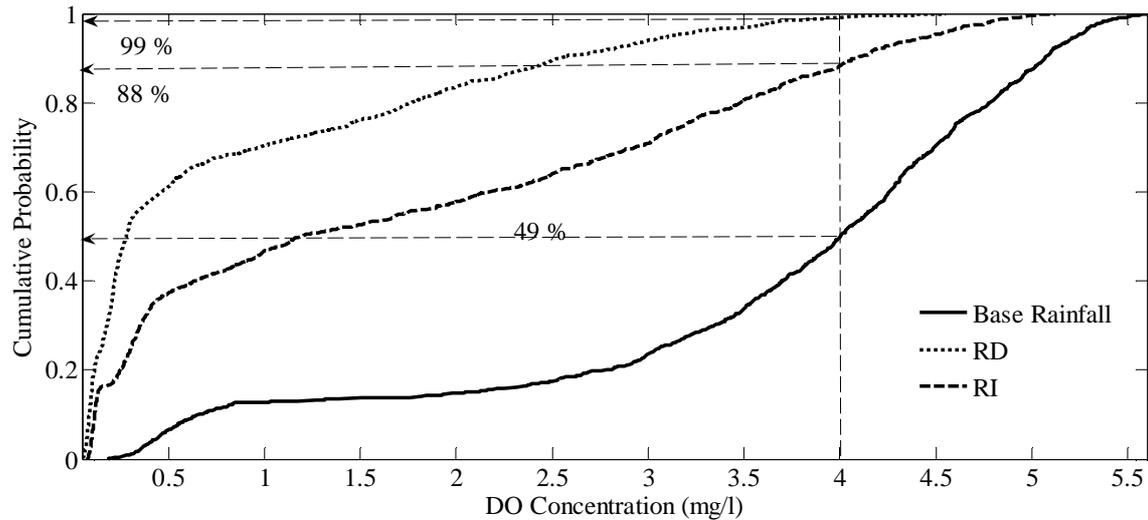
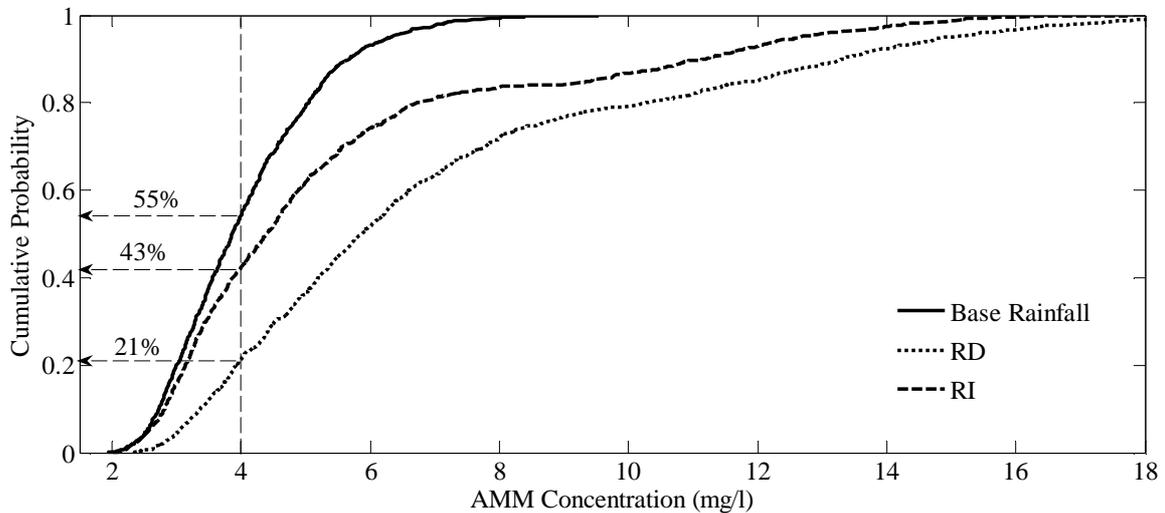


Figure 4.6 Scatter plots between IUWS input parameters (PCW and Q_{maxout}) and water quality indicators (DO and AMM) under climate change parameters (RD and RI)



(a) Empirical CDF of DO concentration



(b) Empirical CDF of AMM concentration

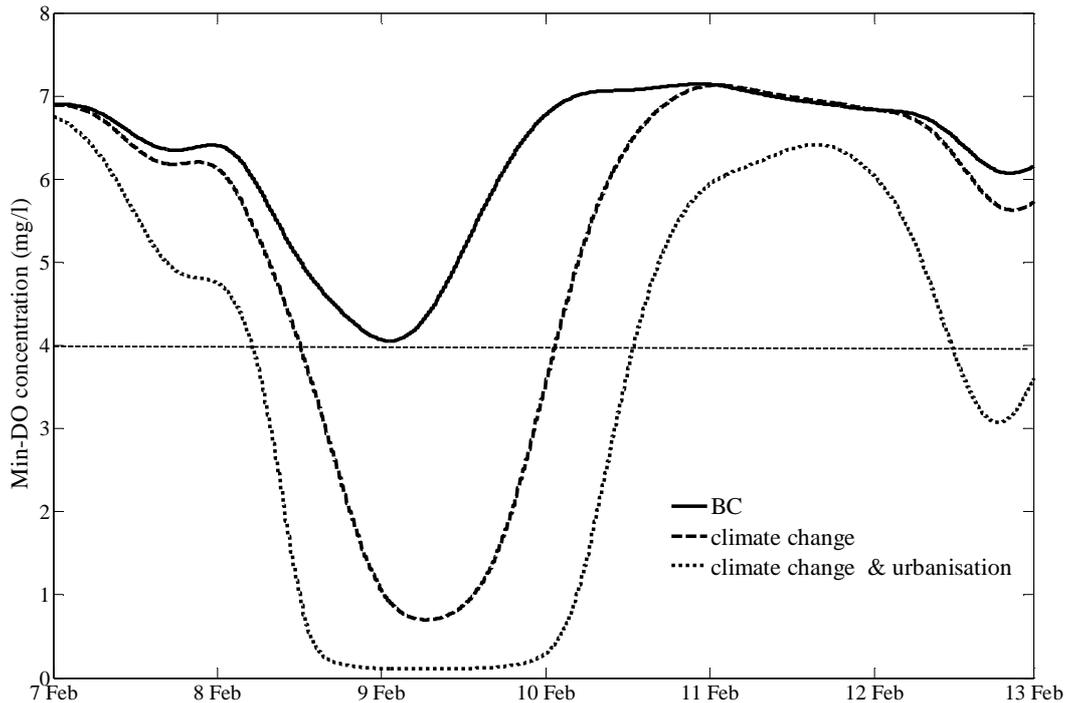
Figure 4.7 Empirical CDFs of water quality indicators in the river under climate change parameters

4.5.6 Existing IUWS Performance under Climate Change and Urbanisation

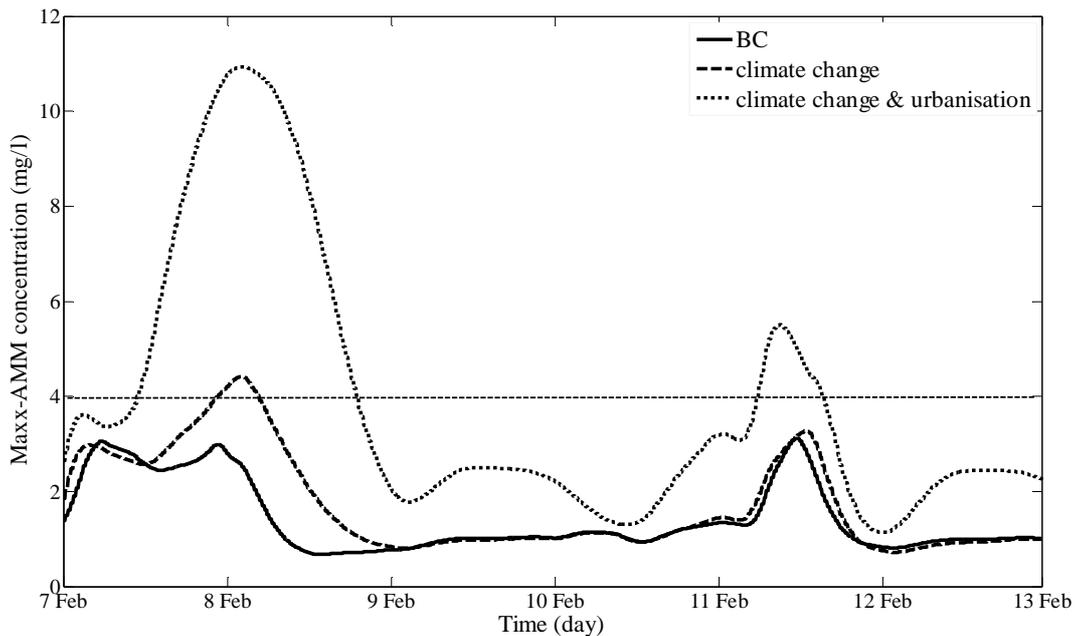
In this section, the existing IUWS performance under RD (i.e. the most sensitive climate change parameter, see section 4.5.3) and combination of RD with the maximum values of urbanisation parameters (see Table 4.1) is evaluated. The aim of this analysis is to evaluate how the existing IUWS may perform under the worst case involving significant climate and urbanisation changes. If the existing IUWS can cope with these changes then fine, otherwise it is likely to have to be upgraded by means of improved operational control and/or system rehabilitation.

Figure 4.8a and Figure 4.8b show the DO and AMM concentrations for 6 days of rainfall at reach 40 and reach 10 of the river under the considered future states respectively. DO and AMM concentrations for the BC are shown with a solid curve and the dashed and dotted curves show the considered climate change and combined climate change with urbanisation, respectively. The dashed line shows the 4 mg/l standard threshold for DO and AMM concentrations.

The results presented in Figure 4.8 show that climate change and urbanisations have the potential to considerably deteriorate the river water quality in the future. This deterioration is a direct consequence of increased loads of pollutants in surface water and wastewater in the combined sewer system resulting from increased DWFs. Note also that combining the urbanisation with climate change further intensifies the water quality deterioration (by increasing further the DWF). Therefore, the existing IUWS with the current operational control strategy is not capable of mitigating the negative effects of future climate and urbanisation changes. As consequence, it should be upgraded by improving operational control and if this is not enough, by re-designing, i.e. rehabilitating the existing system.



(a) DO concentration



(b) AMM concentration

Figure 4.8 Water quality indicators in the BC, under a representative future climate change and under a proposed combination of climate change and urbanisation

4.6 Summary

This chapter investigated the combined impact of urbanisation and climate change on the receiving water quality in the context of an IUWS, together with the ameliorating potential of system operational control. The main conclusions are summarised here below.

Based on the case study results obtained, it can be concluded that climate change is likely to lead to deterioration of water quality in rivers. The potential increase in rainfall depth has a more significant impact on the receiving river water quality than that of rainfall intensity. The results obtained show that the probability of failure (i.e. breach of thresholds of 4 mg/l) for both AMM and DO increased under a changing climate and the failure for the DO is more likely and significant than the one for the AMM.

$Q_{\max\text{out}}$ is the most effective operational control parameter in terms of complying with the DO standard in the river under the climate change scenarios and $Q_{\max\text{in}}$ is the most important operational control parameter in complying with the AMM quality standard in the river. These parameters affect the quality of water in the river by controlling the discharge frequency of the CSOs and storm tank overflows. Q_{trigst} is another operational control parameter that has impact on the DO in the river when RD changes.

Under the conditions of climate change, PCW is the most significant urbanisation parameter because AMM is primarily dependent on it. PCW is also the most important urbanisation parameter influencing the DO quality in the river. The other two important urbanisation parameters are the IMP and the POP.

The results obtained provide a valuable insight into the key urbanisation and climate change parameters impacting on the receiving water quality in the IUWS context. This information can be further utilised to adapt future operation (and, if necessary, design) of these systems which, in turn, should make these systems more resilient to future climate and urbanisation changes.

With regard to the observed worsening of the water quality indicators under the considered climate change and urbanisation parameters, it can be concluded that the current IUWS performance is not efficient in the future to meet the water quality criteria. Therefore improving the systems' operation (and, if necessary, design) is required to achieve the desired performance in the future.

The potential for improved IUWS operational control to mitigate the negative impacts of climate change and urbanisation is analysed in the next chapter where an optimisation based model is built for this purpose and then applied to the analysed case study.

CHAPTER 5

IMPROVED INTEGRATED URBAN WASTEWATER SYSTEM OPERATION

5.1 Introduction

The analyses performed in Chapter 4 have demonstrated that the existing IUWS cannot cope with the envisaged future climate changes and urbanisation in terms of meeting the water quality standards in the recipient. This chapter aims to overcome this problem by improving the operational control of the existing IUWS. This is performed through optimising the operational control of the critical flow rates (see section 4.5.3) in IUWS.

In section 5.2 the operational control optimisation problem is formulated and the optimisation algorithm is introduced. The details of the operational control optimisation objectives and the considered decision variables are introduced in section 5.1.2. The possible features of the future climate changes and urbanisation are considered as some representative scenarios. In section 5.2.2 the details of the aforementioned future scenarios are introduced.

Due to the complexity and time-demanding nature of the IUWS simulation models (which are called about the optimisation process), there is the concern about excessive running times in this study. Therefore in section 5.3 the meta-model MOGA-ANN (Behzadian, *et al.*, 2009; Fu & Kapelan, 2010) is modified and applied in order to substitute with the time consuming simulation model. Section 5.4 will discuss the results obtained from the operational control optimisation of the IUWS (the case study introduced in Chapter 3) for all the defined scenarios. The results achieved show the potential improvements in IUWS operational control under the defined future scenarios.

5.2 Operational Control Optimisation

Optimal operational control of the IUWS aims to derive an operational control strategy to gain the best system performance with respect to various criteria (operation control objectives). Traditionally, these objectives lie in the sewer system or treatment plant due to the limits of separation in modelling of each individual sub-system. These include minimising CSO volume or frequency, and maintaining treatment plant effluent standards. With the development of integrated models, it is now possible to directly use water quality parameters of the receiving water as operational control objectives.

Optimal operational control has received much attention in the context of integrated modelling. For example, Rauch & Harremoës (1999a) considered overflow volume and the mean DO concentration as the objectives. Schütze *et al.* (2002b) considered DO and AMM concentrations as two separated single objectives in the optimisation. In Vanrolleghem *et al.* (2005)'s study, Ammonia concentration was chosen as the objective to derive the optimal control strategy.

In practice an operational control strategy is required to meet multiple and possibly conflicting objectives in order to meet the considered water quality criteria in water recipients. As it is unlikely all the objectives reach their optimum values simultaneously, and only a set of Pareto optimal solutions can be derived where one objective cannot improve without the reduction of at least one of the others.

Therefore optimal control of the IUWS is actually a multiple objective optimisation problem where trade-offs between objectives must be made to obtain satisfactory overall performance in terms of all the considered objectives. Application of multi-objective optimisation methods was introduced by Schütze *et al.* (2002b). Fu *et al.* (2008a) applied the SIMBA tool as the IUWS simulator for multi-objective operational control optimisation. They considered DO and AMM concentrations as the optimisation model objectives.

With regard to these prior studies, this chapter describes the development of a multi-objective operational control optimisation model to improve the IUWS performance. The IUWS simulator tool SIMBA and the case study introduced in Chapter 3 are applied here. Two optimisation objectives, three optimisation

model decision variables (see in section 5.2.1) and six future scenarios (see section 5.2.2) are defined to execute the optimisation process.

5.2.1 Optimisation Problem Definition

With regard to the considered environmental approach of this study, (introduced in Chapter 1), this chapter aims to optimise the system performance directly regarding the indicators of the aquatic life health. There are different types of water quality indicators that can be chosen to improve the quality of water in the river and the choice depends on the problem at hand.

In this study DO and AMM concentrations were addressed as the operational control optimisation objectives for their importance to aquatic life health. This is in accordance with the EU WFD, which aims to achieve “good” ecological and chemical status in all water bodies by 2015 (CEC, 2000). The ultimate aim of the operational control is to maximise the IUWS performance so the objectives of the optimisation algorithm are summarised as:

- Maximise the minimum DO concentration in the river
- Minimise the maximum AMM concentration in the river.

Also, the optimisation is accomplished by optimising the operational control of the critical flow rates as decision variables (with regard to the sensitivity analysis results in section 4.5.4.3) in this study. The defined 4 mg/l thresholds (section 3.3.2) for both DO and AMM concentrations are considered as the water quality standard to protect the aquatic life.

5.2.2 Optimisation Scenarios

The aforementioned optimisation problem is addressed with a scenario-based approach. In this study six scenarios have been developed to describe the possible features of the future climate change and urbanisation with the considered input parameters. These scenarios are divided into two groups; climate change scenarios and combined climate change with urbanisation scenarios. These six scenarios have the potential to indicate the impacts of climate change and urbanisation on the operational control performance of the IUWS in the boundaries of their decision space (input parameters defined in Table 4.1).

Table 5.1 shows the climate change and urbanisation parameters values (see in Table 4.1) for each scenario. Different combinations of these input parameters make the scenarios' structure. The upper and lower values of these urbanisation parameters are shown in Table 4.1.

The operational control optimisation model is applied to each scenario with aim to improve the operational control of the IUWS. For all these scenarios the operational control optimisation objectives and decision variables were defined in section 5.2.1.

Table 5.1 Operational control optimisation model scenarios

Scenarios	Climate Change Parameters	Urbanisation Parameters		
	RD**, RI**	POP (%)	IMP (%)	PCW (l/person/day)
Scenario A (SCA)	Base Rainfall	0*	0*	180
Scenario B (SCB)	RD	0*	0*	180
Scenario C (SCC)	RI	0*	0*	180
Scenario K ₁ (SCK ₁)	RD	1.045	1.05	80
Scenario K ₂ (SCK ₂)	RI	1.045	1.05	80
Scenario L ₁ (SCL ₁)	RD	1.15	1.15	260
Scenario L ₂ (SCL ₂)	RI	1.15	1.15	260

* This means that the urbanisation parameter value is kept at its nominal value (see Table 4.1.)

** This is RD/RI with 30 % increase (see section 4.5.3 and section 4.5.4)

SCA: For this scenario the operational control optimisation is implemented in the base case (BC) aiming to explore the possibility of improving the quality of water in the river in the current operational control settings of the IUWS. All the urbanisation parameters are set to their nominal values (see Table 4.1 for the BC) and the applied rainfall is the base rainfall.

Two climate change scenarios are defined in this study. They aim to investigate the possibility of mitigating the negative impacts of climate change on the quality of water by improving the operational control of IUWS. These scenarios are scenario B (SCB) and scenario C (SCC) as shown in Table 5.1.

SCB: In this scenario the urbanisation parameters are set to their nominal values (see Table 4.1) and the climate change parameter is RD (Table 5.1). This scenario aims to illustrate the operational control potential in the IUWS and reveal the extent of its effectiveness in mitigating the impact of climate change (RD) on river water quality.

SCC: In this scenario the considered urbanisation parameters are similar to SCB. The only difference is the applied climate change parameter RI. This scenario intends to illustrate the existing potential improvements in the water quality by improving the IUWS operational control when rainfall intensity changes.

Four scenarios are defined to describe the possible (extreme) features of the combination of climate change with urbanisation parameters in the future. They aim to investigate the possibility of mitigating the negative impacts of the combined climate change and urbanisation on the quality of water by improving the operational control of IUWS. All these scenarios have the potential to indicate the possibility of concurrent occurrence of the extremes (in order to clarify the boundaries of the objective space) for urbanisation parameters under different climate change parameters.

The aforementioned scenarios are defined as SCK_1 , SCK_2 , SCL_1 , SCL_2 in Table 5.1.

SCK₁: In this scenario the climate change parameter is RD. In addition to the climate change parameter, the urbanisation parameters are added and their combined impacts on the IUWS operational control performance are evaluated. The urbanisation parameters are set to the values presented in Table 5.1. This scenario aims to explore the impending improvements in water quality with optimising the operational control strategies under RD and lower values of the urbanisation parameters.

SCK₂: This scenario is similar to SCK_1 with the difference in climate change parameter considered RI. This scenario aims to investigate the potential of the operational control in the IUWS to mitigate the combined impacts of RI with the lower values of the urbanisation parameters.

SCL₁: This scenario is similar to SCK_1 with the difference being the urbanisation parameters set to their upper values (shown in Table 5.1). This scenario aims to look into the potential of the operational control in the IUWS to mitigate the combined impacts of RD with the upper values of the urbanisation parameters. This scenario is another feature of extreme events under the future changes.

SCL₂: This scenario remains much the same as SCL₁ with the only difference being the climate change parameter considered is RI. This scenario aims to investigate the impending operational control in the IUWS to mitigate the combined impacts of RI with the upper values of the urbanisation parameters.

5.3 MOGA-ANN β Optimisation Algorithm

This section describes the MOGA-ANN β optimisation algorithm used to solve the IUWS operational control optimisation defined in section 5.2.1. The intention was to use the original MOGA-ANN algorithm (Behzadian, *et al.*, 2009) but preliminary tests have shown that algorithm was very time consuming for the use in this study. As a consequence, it was further modified here. As a brief introduction, MOGA-ANN is a multi-objective genetic algorithm coupled with an adaptive neural network. For the purpose of optimisation, NSGA-II was selected in terms of its good performance in solving the multi-objective problems (Deb & Jain, 2002). ANN is used here as a substitution of a full fitness evaluation model to save time. The parameter N_g needs to be defined before starting the search process. This parameter is the minimum size of the (re)training set required for good MOGA-ANN β performance (to be discussed in section 5.3.2). This parameter is achieved by trial and error and is a fixed number in this study.

The size of the (re)training data (N_g) set has considerable impact on the training time and also the accuracy of the predictions. A large training set requires significant computational time. On the other hand, a small training set is likely to lead to poor ANN generalisation. Basically, there are two possible approaches for collecting training data set (Yan & Minsker, 2006): (1) the growing set approach and (2) the fixed set approach. In the first approach, new data are added gradually to the old data and then the network is (re)trained with this new data set. In the second approach less data is normally expected and consequently needs less time for retraining. In this study both approaches are applied to exploit their respective advantages.

5.3.1 Methodology

Figure 5.1 shows the flowchart of the MOGA-ANN β method. As it can be seen from this figure, the search process is comprised of the following steps:

1. Create a random initial population.

2. Evaluate the fitness of each solution (i.e. chromosome) in the population by using the full fitness evaluation model based on the IUWS simulation model.
3. Apply the non-domination sorting algorithm to determine the rank and crowding distance for each chromosome.
4. Save the chromosomes obtained this way (both genes and associated objective function values) into a data set (cache). This data will be used later on for the periodic ANN (re)training and for solution evaluation caching. The cache is updated continuously during the search process, i.e. every time chromosome fitness is evaluated using the full model.
5. Create the offspring population by using the crossover, mutation and selection operators (as in NSGA-II).
6. Check if (re)training data set is full, i.e. if a requested number of samples required for the ANN training have been collected. If not, the algorithm will follow the left arm of the flowchart and the standard process of the NSGA-II optimisation algorithm otherwise it will process to the right arm of the flowchart.

The left arm of the flowchart is continued as long as the required initial training data set are collected. This arm of the flowchart starts from 7 - 13 in Figure 5.1 and then returns to 5-6 and after that the steps 7 - 13 are repeated till becomes greater than the N_g . These steps are explained in the following:

7. Evaluate the offspring generated in step 5 with the full fitness evaluation model (based on the IUWS simulation model).
8. Apply the non-domination sorting algorithm to determine the rank and crowding distance of the offspring generated.
9. Update the cache.
10. Combine the parent population with the offspring generated.
11. Apply the non-domination sorting algorithm to determine the rank and crowding distance for the chromosomes in the combined population.
12. Create the new generation population by keeping the upper half of the ranked combined population.
13. The stopping criterion is checked here. If the stopping criterion is not met the process will be continued.

The right arm of the flowchart is the combination of ANN with the full model i.e. MOGA-ANN algorithm. With regard to the above step 6, if the training size is equal or more than the N_g parameter value, the right arm of the algorithm is started.

14. Check if ANN re-training is required by comparing the number of new data added to the cache with the predefined parameter N_d . N_d is the number of new data re-evaluated using the full fitness evaluation model and is used for triggering ANN re-training.

15. If the new data set size is larger than N_d , the ANN is re-trained and updated otherwise continue at next step.

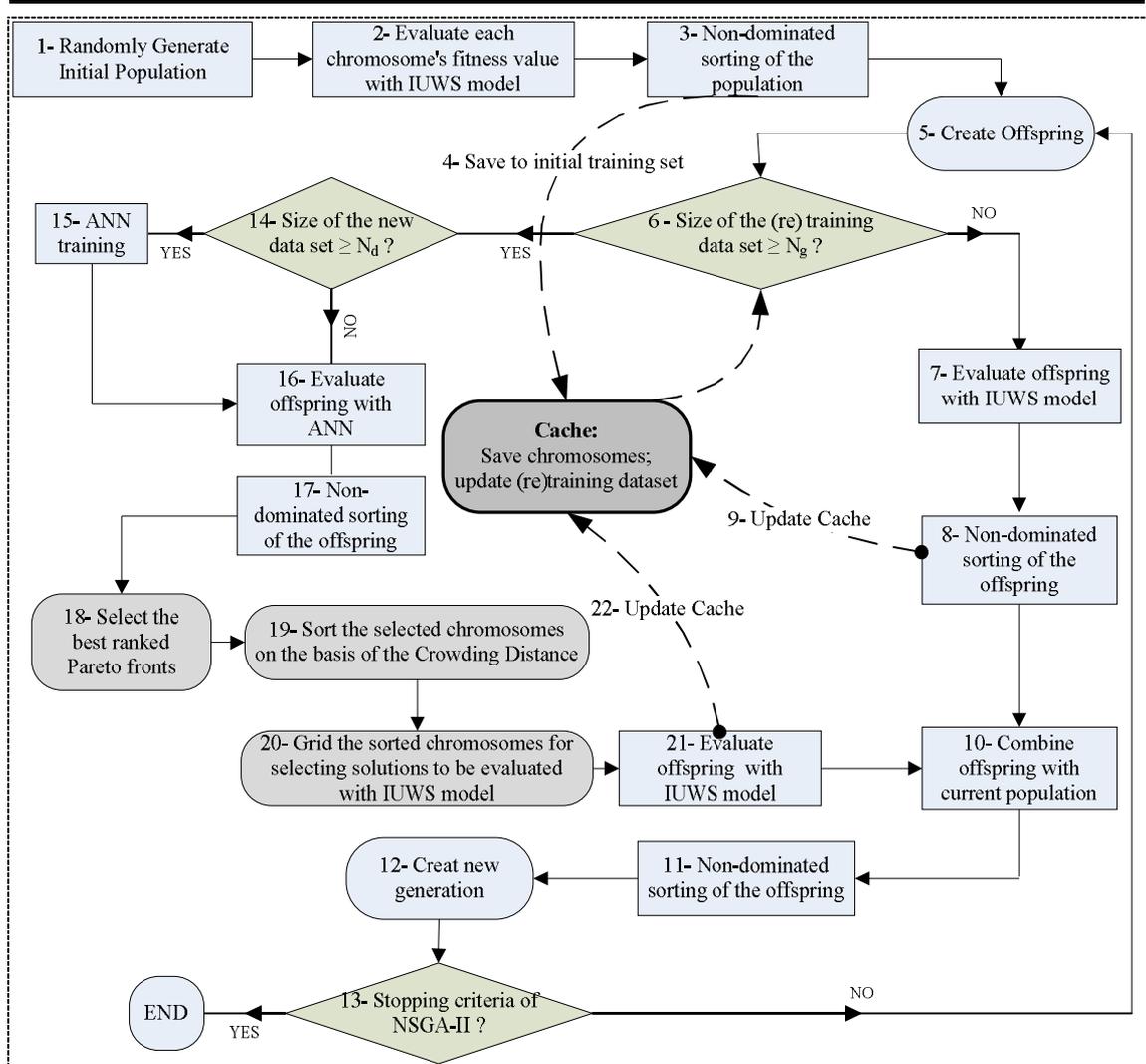
In the optimisation process, ANN can be trained in two different modes, online and offline. In offline training method, the network is trained before the optimisation process starts and then it substitutes the IUWS simulation model. This method usually needs a large amount of samples to provide the required accuracy for its prediction and to cover the whole decision space (Broad, *et al.*, 2010). Therefore the offline training mode is computationally very expensive. Also offline training cannot predict accurately when the objective space moves during the optimisation process. The online training method can overcome the problems of the offline mode and is very efficient in the optimisation processes (Behzadian, *et al.*, 2009; Fu & Kapelan, 2010). With regard to this, the online training mode of ANN is applied in optimisation of the IUWS as the surrogate evaluation engine. These studies show that online training is very effective in saving time whilst keeping accuracy.

16. If the new data set size is less than N_d , the offspring (generated in step 5) fitness function values are evaluated using ANN.

17. Apply the non-domination sorting of the offspring to determine the rank and crowding distance of each chromosome.

18. To ensure that the search process continues toward identifying Pareto optimal solutions, the best chromosomes identified so far are re-evaluated by using the full fitness evaluation model. In the original MOGA-ANN method, the best chromosomes to re-evaluate are identified as the ones belonging to the latest Pareto-front (i.e. all solutions with rank equal to one).

19. However, it was found out during initial tests that for the problem analysed it is not uncommon for all solutions in the population to have the same rank (i.e. rank 1). To resolve this issues, another, new criterion was developed for selecting the best chromosomes for full fitness reevaluation. The new criterion sorts first the chromosomes with rank equal to 1 in descending order of their crowding distances.
20. Once this is done, the sorted chromosomes are classified into several groups of same size, each containing a specified number of solutions. Different group sizes were tested in this study. Larger group sizes did not show accurate results (comparing to the results obtained from original NSGA-II) and smaller group sizes need high computational time. Finally, the group size of four is chosen for the case study as it represents more accuracy with acceptable computational time. Then one chromosome from each group is selected randomly for re-evaluation with the IUWS model. This helps reducing the computational time. Consequently, MOGA-ANN β helps better generalizing the original MOGA-ANN algorithm (Behzadian, *et al.*, 2009; Fu & Kapelan, 2010).

Figure 5.1 Flowchart of the MOGA-ANN β algorithm

21. Re-evaluate the offspring generated by using the full fitness evaluation model.

22. Update the cache with chromosomes re-evaluated in the previous step.

This can be done using one of the following two different approaches (Yan & Minsker, 2006): (1) the growing data set approach and (2) the fixed data set approach. In the former approach, both new and existing data is collected and then used for ANN retraining whilst in the latter approach existing data are replaced with new data (leading to the constant number of retraining data and hence, smaller data sets than in the growing set approach). Thus, the fixed set approach typically leads to less time required for the ANN retraining and contains less data but may also lead to lower prediction accuracy. A mix of the above two approaches is adopted here to exploit the benefits of both. The growing

set approach is used first to gather (re)training data required and the fixed set approach applied when replacing the oldest existing data, which are less likely to be found by the genetic algorithm search, with the new data.

The ANN in this study has three layers: input layer, hidden layer and output layer. The input layer is set exactly with the input variables (decision variables of the optimisation model) and therefore the number of its neurons is equal to the number of input variables. The output layer has two neurons which represent the number of optimisation objectives in this study. A sigmoid function is considered as the transform function for hidden layers and a linear transfer function for the output layer. In this analysis to improve the performance of the ANN, the inputs and outputs are normalized into the interval [0, 1]. Then the outputs are again transformed to real values after estimations. The Bayesian regularization back propagation method is used for its accurate predictions in training (Alvisi & Franchini, 2011; Ha & Stenstrom, 2003; Malekmohammadi, *et al.*, 2009). This training method is a difference between the original MOGA-ANN and MOGA-ANN β . A batch mode of training is applied to enter the inputs to the network before the weights are updated.

5.3.2 MOGA-ANN β Performance Validation

The performance of the MOGA-ANN β algorithm is validated here on the case study introduced in Chapter 3. In this study, SCB (introduced in section 5.2.2) is used to set the IUWS model input parameters as the initial tests showed that in SCB,DO and AMM concentrations have larger value ranges than in SCA (discussed in Chapter 4). Therefore the ANN is better trained and consequently generalizes the MOGA-ANN β performance. The operational control optimisation problem objectives and decision variables are the same as section 5.2.1. The ANN used in the MOGA-ANN β algorithm has three inputs corresponding to three operational control parameters defined in section 5.2.1. The number of neurons in the hidden layer is set to 20 with trial and error (see Figure 5.2). The training accuracy is 0.001 and the maximum number of epochs is 1300 to meet the network performance goal (achieved by trial and error).

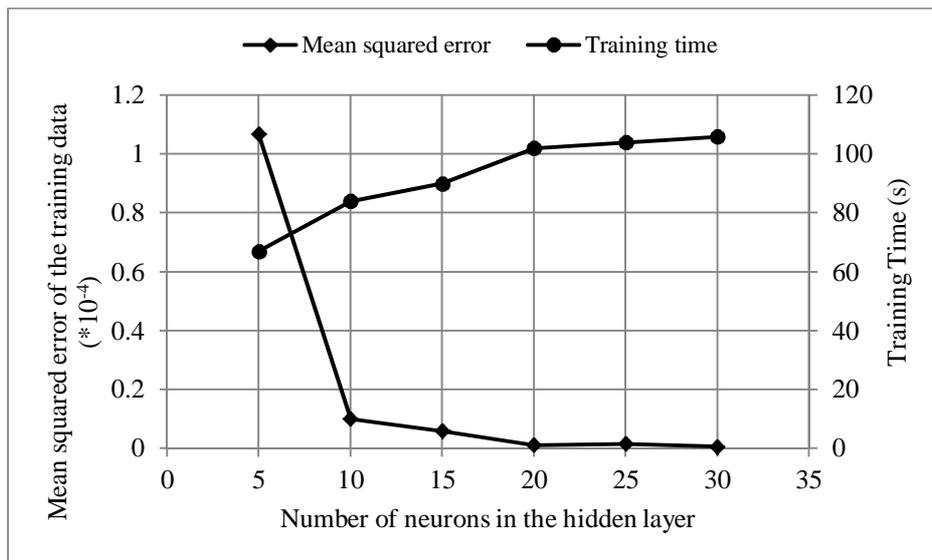


Figure 5.2 Selection of the number of neurons in the hidden layer

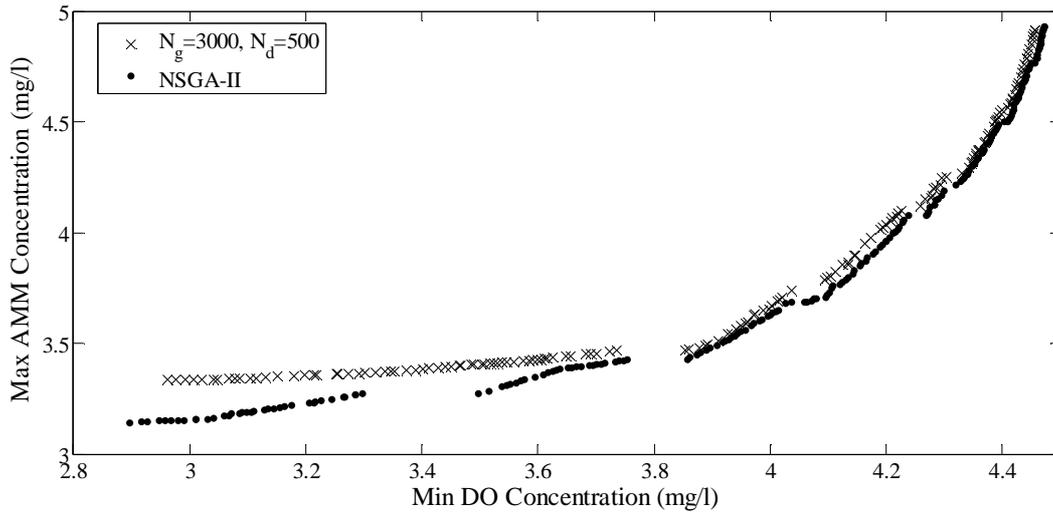
In line with the trials and errors carried out to find the best network parameters (with enough accuracy and acceptable training time), here the efforts to find the number of neurons in the hidden layer for training of the network is presented in Figure 5.2. The numbers of neurons in the hidden layer have impact on the accuracy of the future network predictions and also on the training time as well. Therefore finding proper number of neurons for the hidden layer is important. For this purpose 5, 10, 15, 20, 25 and 30 neurons for the hidden layer were considered and tested in terms of their mean squared errors (*mse*) and also training time. The smaller *mse* value and less training time, is desirable but normally both does not happen together. As it can be observed in Figure 5.2, after 20 neurons in the hidden layer, the *mse* does not change significantly. Similar observation exists about the training time after 20 neurons in the hidden layer. Hence although 5, 10 and 15 neurons have less training time in comparison with 20, 25 and 30 neurons but their *mse* values are considerable which is not desirable. As a result the number of 20 neurons in the hidden layer is selected with regard to its small *mse* value and acceptable training time (in comparison with the minimum training time for 5 neurons).

Neural networks exhibit a major drawback similar to linear methods of function approximation: they cannot extrapolate. This is due to the fact that a neural network can map virtually any function by adjusting its parameters according to the presented training data. For regions of the variable space where no training data is available, the output of a neural network is not reliable. In order to

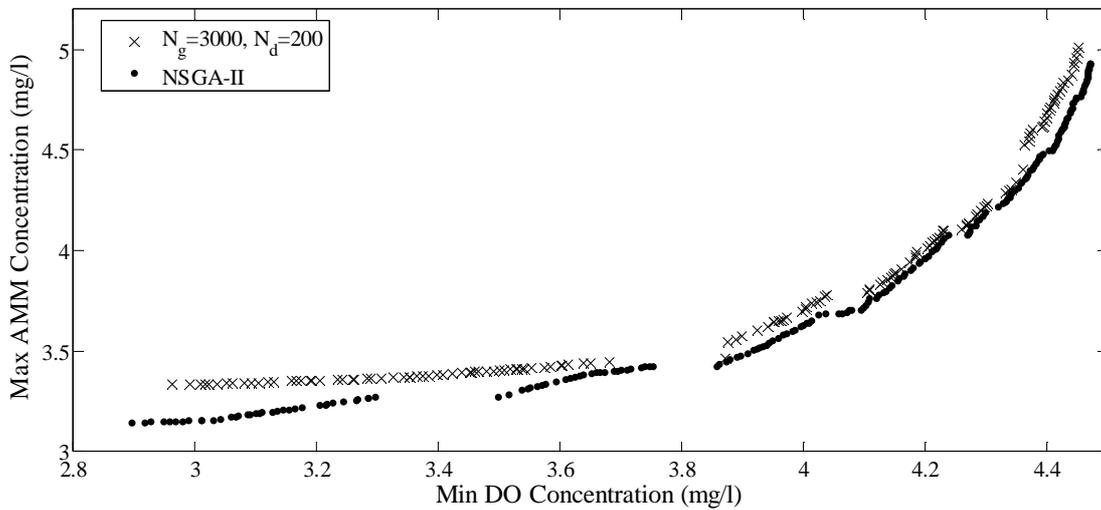
overcome this problem, one should in some form record the range of the variable space where training data is available. It should note here that in this study such an experience/issue during the training process was not observed.

Additionally the performance of the MOGA-ANN β is evaluated by solving the above problem by NSGA-II too and then comparing the results. The Pareto-fronts obtained using these two optimisation methods have been compared by using two well-known performance indicators: S-metric index (Fernandez, *et al.*, 2009) and Epsilon indicator (Zitzler, *et al.*, 2003). The S-metric (also known as the Hypervolume index) indicates both the diversity and the closeness of the solutions to the true optimal Pareto-front. Epsilon indicator is defined as the minimum value that an optimal Pareto-front needs to be translated to, in order to completely dominate the reference Pareto-front. The performance indicator values of the optimal Pareto-fronts in all the tests are compared together in order to find the best performance of the model. In this study the population size and the number of the generations used in the optimisation process are both set equal to 200. Three MOGA-ANN β training set sizes (N_g equal to 1000, 2000 and 3000 samples) and three new data set sizes (N_d equal to 50, 200 and 500) have been tested here.

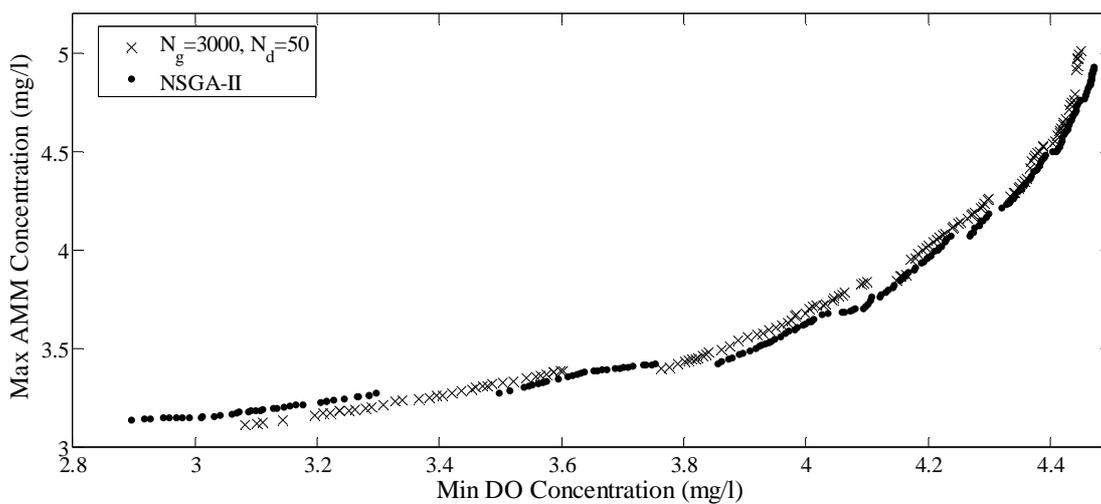
Figure 5.3 shows the selected optimal Pareto-fronts obtained using the MOGA-ANN β method for $N_g=3000$ and N_d equal to 50, 200 and 500. All three figures demonstrate that the obtained MOGA-ANN β Pareto-fronts represent good approximations of the corresponding NSGA-II Pareto-fronts. The same figure also demonstrates that the best results are obtained for $N_d=50$ (Figure 5.3c). In other words, better results can be obtained by more frequent ANN training.



(a) Comparison for $N_g=3000$ and $N_d=500$



(b) Comparison for $N_g=3000$ and $N_d=200$



(c) Comparison for $N_g=3000$ and $N_d=50$

Figure 5.3 Comparisons of optimal Pareto-fronts between NSGA-II and the MOGA-ANN β model

The computer power used in this research study was an intel(R) Core(TM)2 Quad CPU, with a [Q8300@2.5](#) GHz processor. So with this computer power and the 200 generation and population size used in this study, the initial computational time (before using the MOGA-ANN β method) was about 5 days and 12 hours. Therefore with regard to the numbers of the future scenarios which had to be tried and also the trials and errors required in this study, it was necessary to reduce the computational time.

Figure 5.4 shows the computational time savings obtained which is saved for different sets of MOGA-ANN β parameters when compared to the NSGA II. As it can be observed in all sets of parameters, nearly above 60% of computational time is saved (i.e. about 3 days and 8 hours). With reference to Figure 5.4, among all sets of surrogate model parameters, $N_g=3000$ and $N_d=50$ indicate the best performance with saving nearly 70% computational time (i.e. about 3 days and 19 hours). In other words the MOGA-ANN β can obtain similar Pareto optimal front as the NSGA-II optimal Pareto-front, but with significantly less computational time.

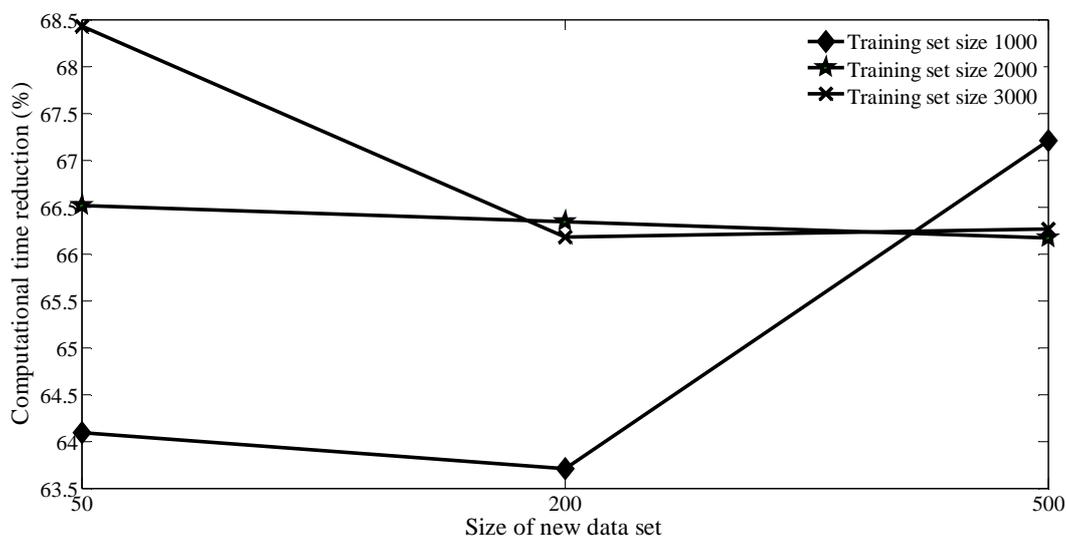


Figure 5.4 Computational time reduction (%)

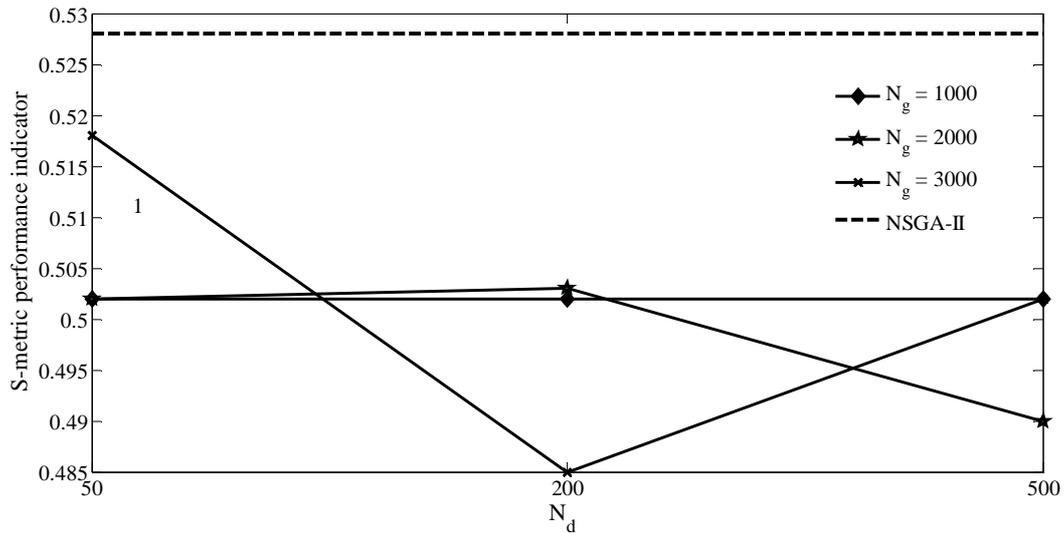
For the further evaluation of the MOGA-ANN β performance, the aforementioned S-metric index was calculated for the $N_d=50$ with different N_g sizes (see Figure 5.5a), as indicated the best performance in Figure 5.3c (comparing to $N_d=200$ and 500). According to the definition of the S-metric index (Fernandez, *et al.*, 2009), selecting a good reference point depends on the minimisation and/or maximisation of the objectives considered. As in this study one objective is

minimised (i.e. AMM concentration) and the other is maximised (i.e. DO concentration), the reference point is considered in a way that the larger S-metric value represents better performance.

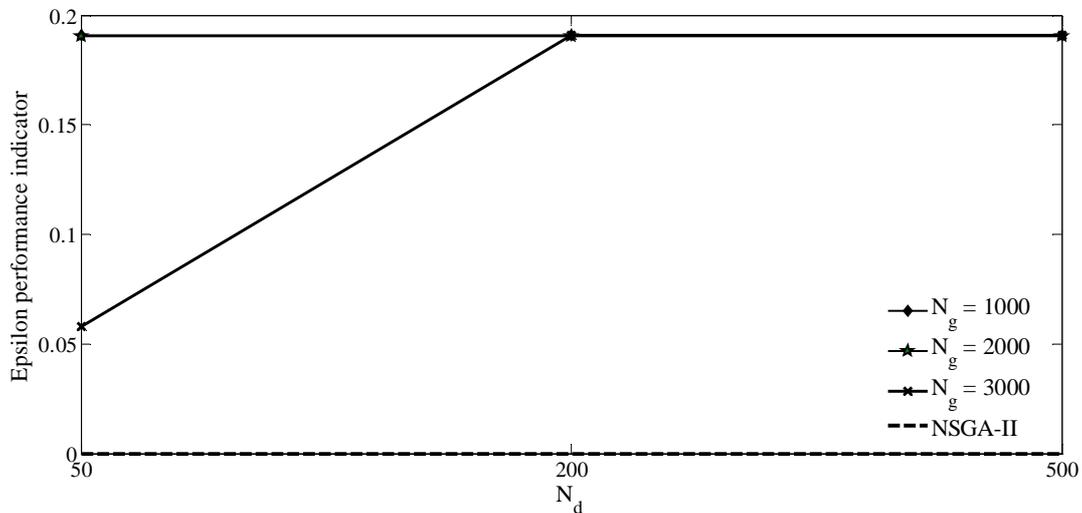
It can be observed in Figure 5.5a that $N_d=50$ with $N_g=3000$ samples is closer than the other sets ($N_g=1000$ and 2000) to the NSGA-II (dashed line).

In addition to the S-metric index, another performance indicator can lead to better identification of the best parameter sets to evaluate the MOGA-ANN β performance. Figure 5.5b shows the Epsilon indicator for the mentioned training sets. Note that the smaller the Epsilon indicator value, the better the results. With regard to Figure 5.3, the closer the optimal Pareto-fronts resulting from the MOGA-ANN β and NSGA-II methods, the better the performance of the MOGA-ANN β method. Equally, the smaller the distance between the dashed line and other lines in Figure 5.5b, the better the performance of the MOGA-ANN β method. As it can be seen from this figure, the aforementioned parameter set ($N_g = 3000$ and $N_d = 50$) is the best performing parameter set.

Based on the above results obtained, it can be concluded that larger training sets (i.e. $N_g=3000$) with more frequent re-training (i.e. $N_d=50$) lead to improved performance of the MOGA-ANN β method.



(a) S-metric performance indicator



(b) Epsilon indicator performance indicator

Figure 5.5 MOGA-ANN β performance indicators

5.4 Optimisation Results and Discussion

5.4.1 Climate Change Scenarios

The operational control optimisation was applied for the climate change scenarios (SCB and SCC). Figure 5.6 shows the Pareto-fronts representing optimal trade-off between minimum DO and maximum AMM concentrations for SCA, SCB and SCC. The point 'BC_{SCA}/BC' shows the performance of the IUWS under the base case defined in section 3.3.2 (which assumes existing operational system control and no climate change/urbanisation related changes). The BC_{SCB} and BC_{SCC} show the performance of the IUWS with existing operational control and under scenarios SCB and SCC respectively.

Figure 5.6 shows clearly that point 'BC_{SCA/BC}' is dominated by the optimised solutions obtained in SCA. This demonstrates that optimising the operational control has the potential to substantially improve the quality of water in the river under base rainfall (scenario SCA). Also the points BC_{SCB} and BC_{SCC} are dominated by the solutions obtained under increased rainfall depth (SCB) and also increased rainfall intensity (SCC). The reason for the improvements for the SCB is that increasing the rainfall depth in SCB has more potential to worsen the quality of water in the river than increasing the rainfall intensity in SCC and base rainfall in SCA. This is in line with sensitivity analysis results reported in sections 4.5.3 and section 4.5.4.

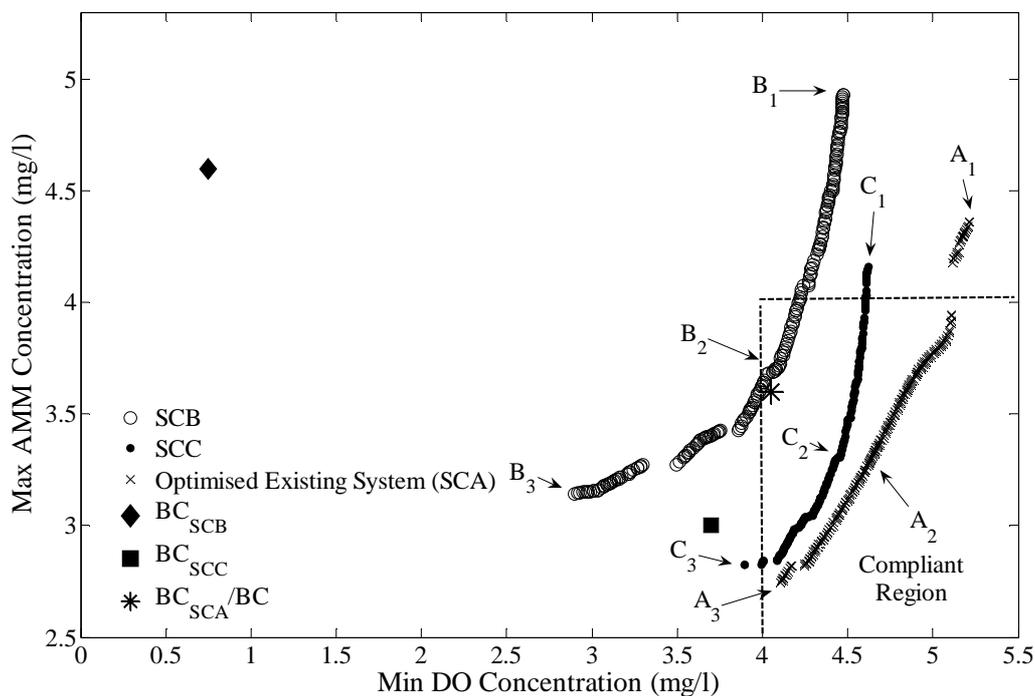


Figure 5.6 Optimal Pareto-front for SCB, SCC and SCA

The solutions at the right end of each trade-off curve (A₁, B₁ and C₁) represent operational control strategies with the highest minimum DO concentrations and the highest maximum AMM concentration in the river. Through the optimisation process the AMM concentration is improved in SCA, SCB and SCC down to the solutions at the other end with minimum AMM concentration (A₃, B₃ and C₃) and minimum DO concentration. In other words it is impossible for a solution to achieve both “good” DO and AMM concentration at the same time. Understanding this concept of trade-off will help decision makers understand the implications of an operational control strategy and system control better. In all the three scenarios (SCA, SCB and SCC) none of the solutions is absolutely

better than others in terms of DO and AMM concentrations. Therefore selecting an operational control strategy among the other ones is quite subjective and depends on the decision maker's preference.

In line with helping decision makers to select an appropriate operational control strategy the water quality criteria 4 mg/l (introduced in section 3.3.2) is applied here to limit the number of preferred solutions in each scenario. The region limited to the 4 mg/l concentration indicates the “*compliant region*” which solutions in this region can meet both DO and AMM concentrations standards (FWR, 1998). These solutions should be preferable by decision makers. With regard to the optimal Pareto-fronts in SCB and SCC, it can be observed that numbers of the solutions within the *compliant region* decrease significantly in SCB in comparison with SCA and SCC. This indicates that the decision makers have fewer options in SCB to choose an appropriate operational control strategy in the future.

5.4.2 Combined Climate Change and Urbanisation Scenarios

Figure 5.7 shows the optimal Pareto-fronts obtained for optimisation scenarios SCK_1 and SCK_2 . As before, point BC/BC_{SCA} shows the min-DO and max-AMM concentrations obtained in the base case scenario (assuming no climate nor urbanisation changes and existing system operational control). The BC_{SCK_1} and BC_{SCK_2} points show the min-DO and max-AMM concentrations in the river under scenarios SCK_1 and SCK_2 respectively. The aforementioned points indicate that the system under SCK_1 fails to meet the DO concentration standard (i.e. 4 mg/l) and in SCA and SCK_2 can only roughly meet it. Therefore this indicates that the system improvement under the aforementioned scenarios is required.

As it can be observed in Figure 5.7, BC_{SCA}/BC , BC_{SCK_1} and BC_{SCK_2} are dominated by the respective optimal Pareto-fronts containing solutions with improved operational control. It can be also seen from Figure 5.7 that the optimal Pareto-front for SCA is dominated by the Pareto-fronts obtained for SCK_1 and SCK_2 . The reason for this can be explored in the significant reduction of PCW from its nominal value in SCA (180 l/person/day) to its minimum value in SCK_1 and SCK_2 (80 l/person/day) under both climate change parameters. Therefore, the reduction in PCW (as the most sensitive urbanisation parameter – see Chapter 4) has the potential to improve the quality of water in the recipient. Also, note that most of the obtained operational control strategies in

these two scenarios are within the *compliant region*, i.e. satisfy the water quality standards. This indicates that SCK_1 and SCK_2 need less operational control interventions than SCA to get into this region.

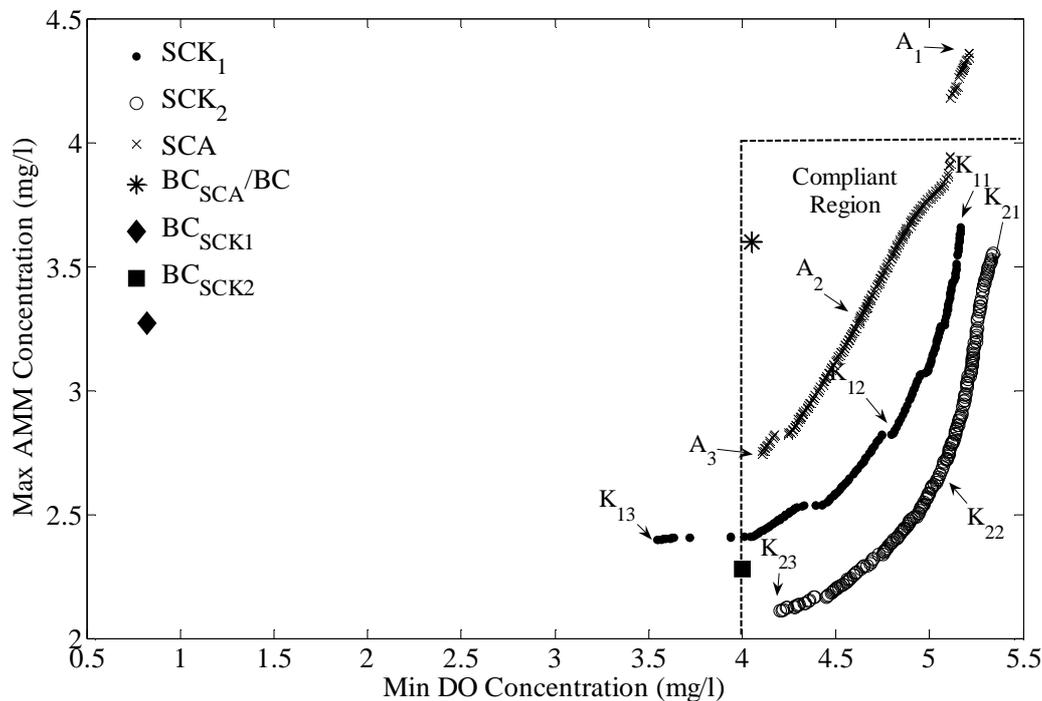


Figure 5.7 Optimal Pareto-front for SCK_1 and SCK_2

These water quality improvements in SCK_1 and SCK_2 (when compared to SCA and BC/BC_{SCA}) can be explained by the reduction in pollutants' load. DoE (1992) showed that 95% of PCW is returned to the sewer systems as wastewater in the UK. Therefore reduction of PCW (the most effective urbanisation parameter on the quality of water shown in section 4.5.4.2) in SCK_1 and SCK_2 from 180 l/person/day (in the BC/BC_{SCA} and SCA) to 80 l/person/day (minimum value range shown in Table 4.1) reduces the pollutants' load in the wastewater despite of changing the climate and minimum increase for the other urbanisation parameters (see Table 4.1). Also it indicates that controlling the urbanisation growth in the future has significant impact on the performance of the system in terms of satisfying the water quality standards. This provides more options for the decision makers to choose suitable operational control strategies for the IUWS.

The optimal Pareto-fronts containing solutions with improved IUWS operational control under SCL_1 and SCL_2 scenarios are shown in Figure 5.8. However, as it can be seen from this figure, unlike in SCK_1 and SCK_2 , the obtained optimal Pareto-fronts for SCL_1 and SCL_2 are still not within the compliant region. In

other words, despite the improved operational control, the IUWS cannot cope with the future changes described in these two scenarios. Similarly to SCK_1 and SCK_2 , the reason of this considerable worsening in river quality has to be linked to the urbanisation parameter PCW. In these two scenarios this parameters has the upper value range of PCW (260 l/person/day shown in Table 4.1) which is 60% more than its nominal value (180 l/person/day shown in Table 4.1). With regard to DoE (1992) study, this significant increase of PCW increases the pollutants' load in the wastewater and consequently leads to deterioration of water quality in the river.

When compared to scenarios SCK_1 and SCK_2 , the IUWS performance with climate and urbanisation changes assumed in scenarios SCL_1 and SCL_2 shows more significant deterioration in the river water quality under existing operational control (see points BC_{SCL_1} and BC_{SCL_2} in Figure 5.8). This indicates that the system needs further improvement to cope with the future changes assumed in these two scenarios.

Figure 5.8 shows also that in SCL_1 water quality deteriorates considerably more than in SCL_2 . This is due to increased negative impacts of urbanisation parameters under RD in SCL_1 .

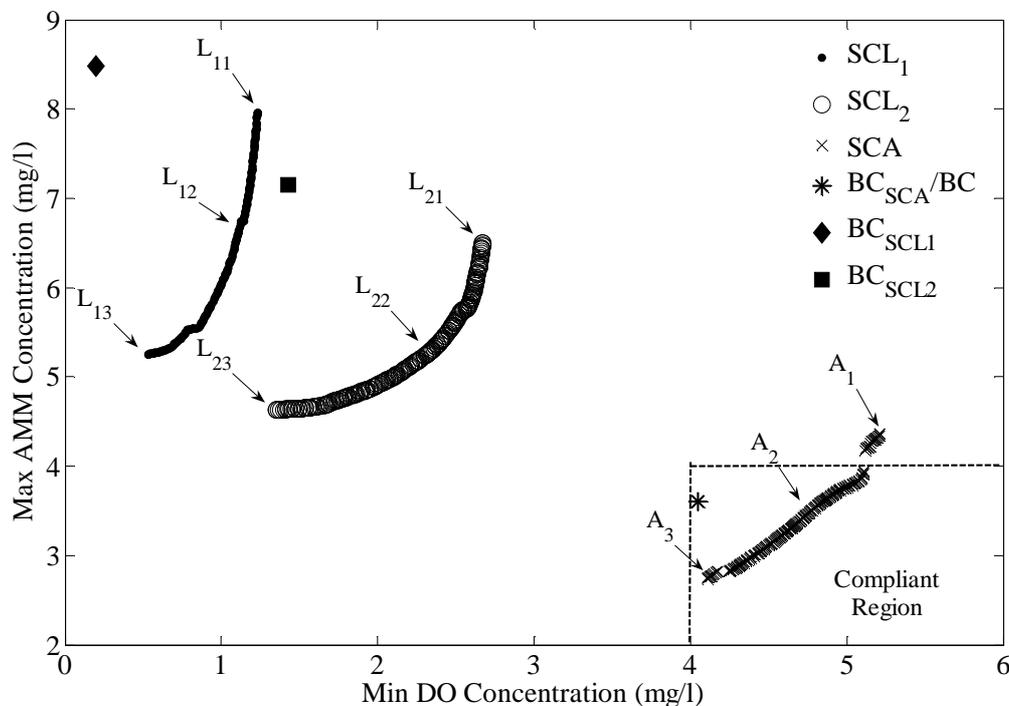


Figure 5.8 Optimal Pareto-front for SCL_1 and SCL_2

The solutions at the right ends of Pareto-fronts (K_{11} , K_{21} , L_{11} and L_{21}) and corresponding left ends (K_{12} , K_{22} , L_{12} and L_{22}) present an operational control strategy with the highest (minimum) DO concentration and the lowest (maximum) AMM concentration in the river. Similar to climate change scenarios, the system performance through multiple objective optimisation, can be improved in terms of both DO and AMM concentrations under the future climate changes. The same as climate change scenarios, it is impossible for a solution to achieve DO and AMM compliance at the same time. As in SCK_1 and SCK_2 all the solutions are within the *compliant region*, the decision makers have larger decision space to select a desirable operational control strategy to satisfy the water quality under the future changes described under these two scenarios. In SCL_1 and SCL_2 there is no desirable solution for decision makers. Therefore, in these cases, changing the operational control of the IUWS only, (even by optimisation) cannot improve water quality in the river to the target level.

5.4.3 Comparison of Solutions Obtained in Different Scenarios

5.4.3.1 Comparing the Operational Control Strategies

With regard to the achieved optimal Pareto-fronts for all the scenarios (section 5.4.1 and section 5.4.2), it is important to look into the details of the individual solutions obtained, i.e. the optimised operational control parameter values: $Q_{\max\text{out}}$, $Q_{\max\text{in}}$ and Q_{trigst} . When doing so, all the solutions within the *compliant region* are selected as they are likely to be selected by any decision maker. For SCA, SCB, SCC, SCK_1 and SCK_2 these solutions exist (Figure 5.6 and Figure 5.7) but in SCL_1 and SCL_2 all their solutions are selected as their optimal Pareto-fronts' cannot meet the *compliant region* (see Figure 5.8).

Figure 5.9, Figure 5.10 and Figure 5.11 display the values of the abovementioned operational control parameters for the aforementioned selected solutions in each scenario. Note that in Figure 5.9, Figure 5.10 and Figure 5.11, the horizontal axis indicates the operational control parameters and the vertical axis shows their corresponding values. The lines with the descending slope from $Q_{\max\text{out}}$ to $Q_{\max\text{in}}$ present the system performance in reducing the CSOs considering the treatment capacity of the WWTP. Also the lines with the ascending slope from $Q_{\max\text{in}}$ to Q_{trigst} show the system efforts to store more wastewater in the storm tank to be partially treated by sedimentation. The dashed lines show the values of the operational control

parameters in the BC. The role of the operational control parameters; $Q_{\max\text{out}}$, $Q_{\max\text{in}}$ and Q_{trigst} in the IUWS performance was illustrated in section 4.4.1.3. The following conclusions can be obtained from Figure 5.9, Figure 5.10 and Figure 5.11 for the operational control parameters.

Generally the increase of $Q_{\max\text{out}}$ close to its maximum value (see Table 4.1), compared to the BC and SCA, indicates the IUWS performance to control the CSOs prompted by climate change and urbanisation. Additionally the increase of wastewater volume under RD in SCB and SCK_1 (Figure 5.9b and Figure 5.10a) requires additional operational control (i.e. greater $Q_{\max\text{out}}$) than under RI in SCC and SCK_2 (see Figure 5.9c and Figure 5.10b) to maintain the water quality standards. This is compliant with the sensitivity analysis results shown in section 4.5.3 and section 4.5.4. In SCL_1 and SCL_2 , despite reaching the maximum value of $Q_{\max\text{out}}$, the optimal operational control strategies obtained (see Table 4.1 and Figure 5.11) are not good enough to meet the *compliant region*. In other words in addition to climate change, maximum values of the urbanisation parameters (considered in these two scenarios) intensify the deterioration of water quality in the river by increasing the CSOs' frequency and volume. Therefore, the IUWS requires being re-designed under these two scenarios. As there is an interaction between $Q_{\max\text{out}}$ and $Q_{\max\text{in}}$ (Fu, *et al.*, 2009), therefore any changes in the $Q_{\max\text{out}}$ can affect the $Q_{\max\text{in}}$.

The $Q_{\max\text{in}}$ parameter value increased in all scenarios when compared to the BC. The reason for this is that the system tries to convey more wastewater discharged from the sewer system to the WWTP to be treated. Furthermore it reduces the pollutants' load by reducing the storm tank overflows. In spite of the climate change scenarios (i.e. SCB and SCC) which $Q_{\max\text{in}}$ does not have considerable changes comparing to SCA, the volume of wastewater increased under the combined scenarios (i.e. SCK_1 , SCK_2 , SCL_1 and SCL_2), brings about greater changes (i.e. between its minimum and maximum value ranges) (see Table 4.1) comparing to SCA (Figure 5.9a) to meet the *compliant region*. Also the decrease of $Q_{\max\text{in}}$ indicates the need to store more wastewater into the storm tank, to be partially treated by sedimentation. The abovementioned system performances also can be observed in SCL_1 and SCL_2 as shown in Figure 5.11, but all this is not sufficient to reach the *compliant region* (see Figure 5.8).

The existing interaction between the Q_{trigst} parameter and the Q_{maxin} controls the storm tank performance (see section 4.4.1.3). The increase of Q_{trigst} releases more wastewater inflow to the WWTP for treatment and its decrease causes more frequent emptying from the storm tank to reduce the storm tank overflows. The changes of Q_{trigst} are different in each scenario comparing to the BC and SCA (see Figure 5.9a). For example for SCB, SCL_1 and SCL_2 (Figure 5.9b, Figure 5.11a and Figure 5.11b) it is near to the upper value range (Table 4.1) to inflow the increased wastewater volume to the WWTP for treatment but in SCK_1 and SCK_2 , with less wastewater volume, it behaves different.

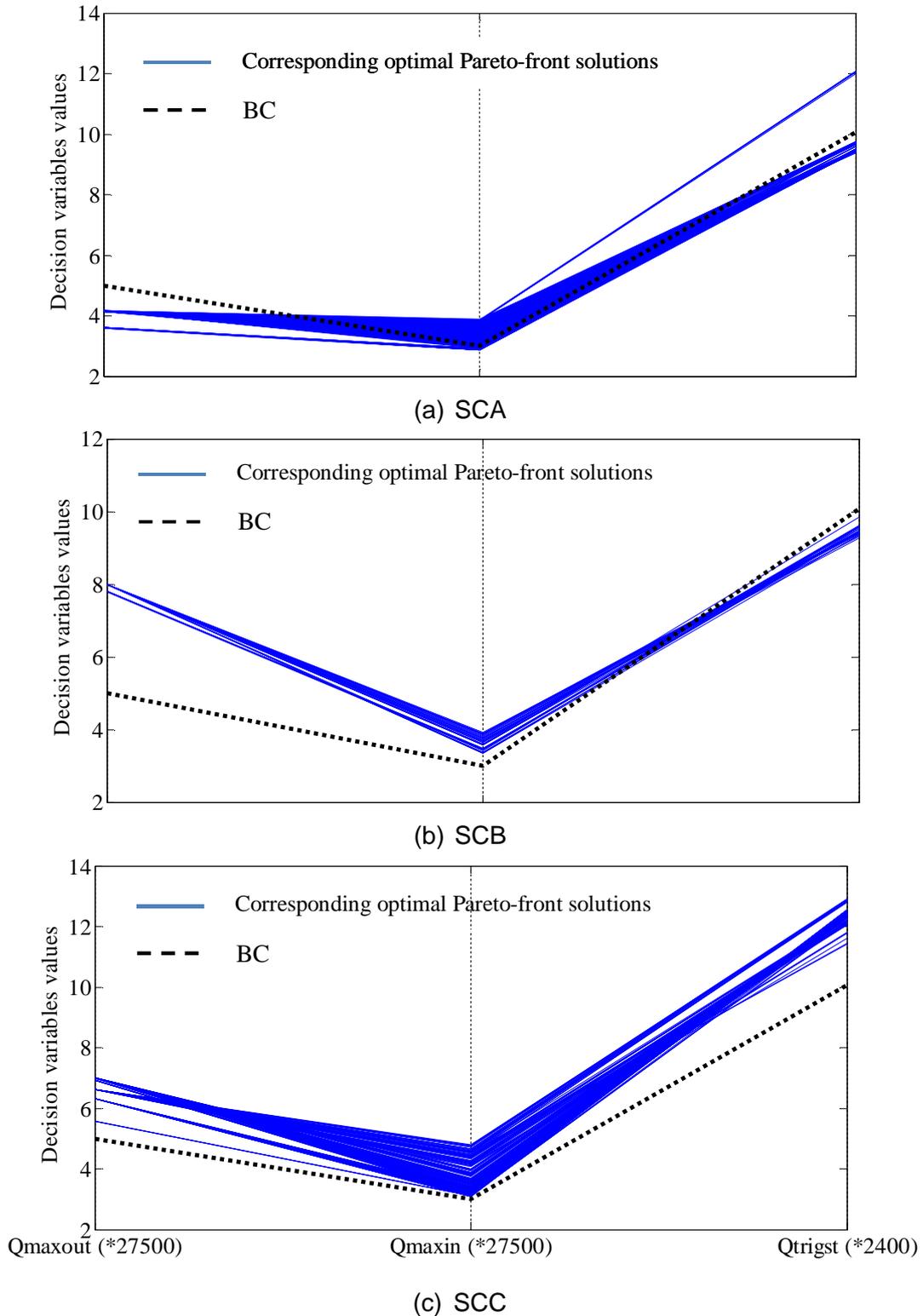


Figure 5.9 Operational control parameters of the solutions within the compliant region; (a) SCA, (b) SCB, (c) SCC

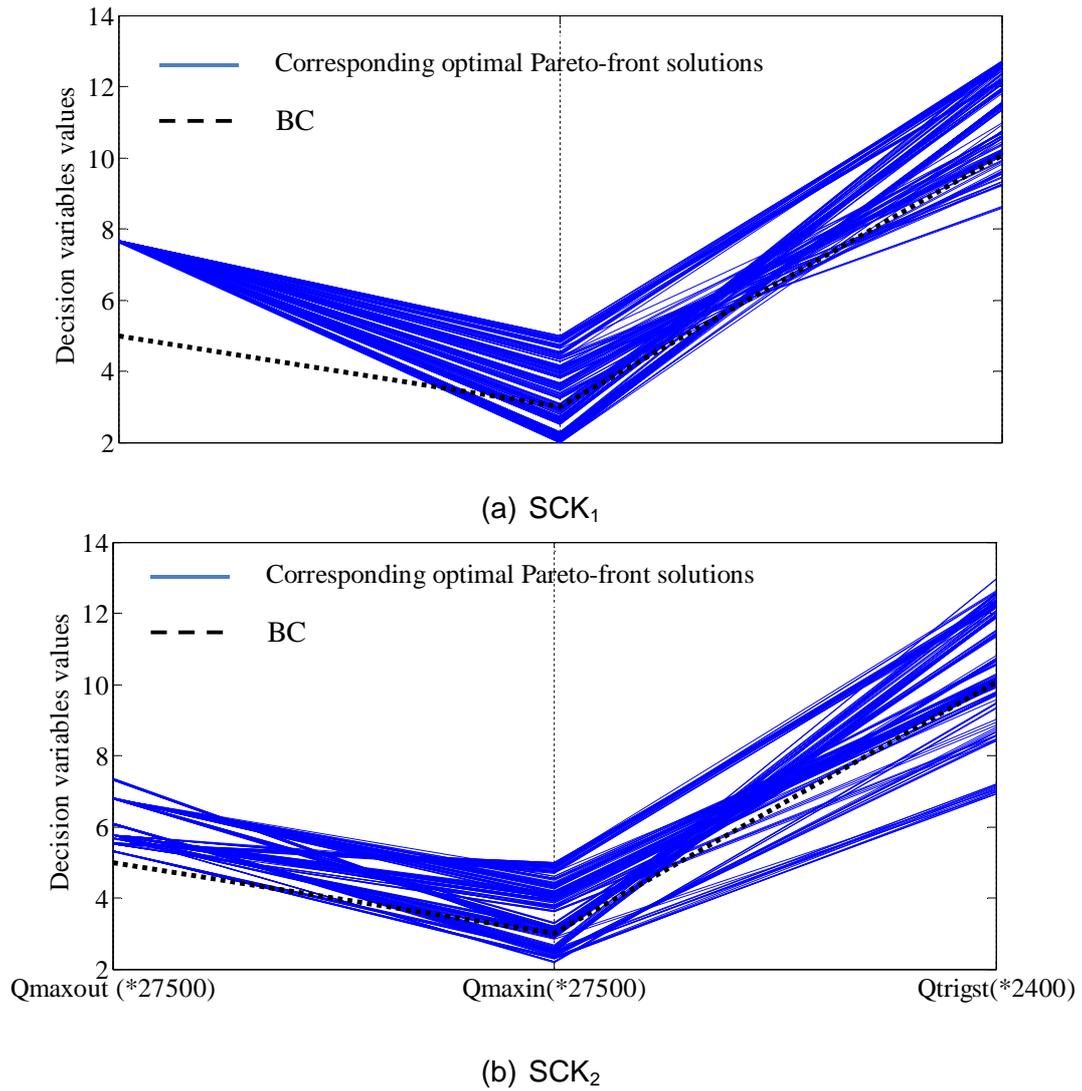


Figure 5.10 Operational control parameters of the solutions within the compliant region in SCK₁ and SCK₂

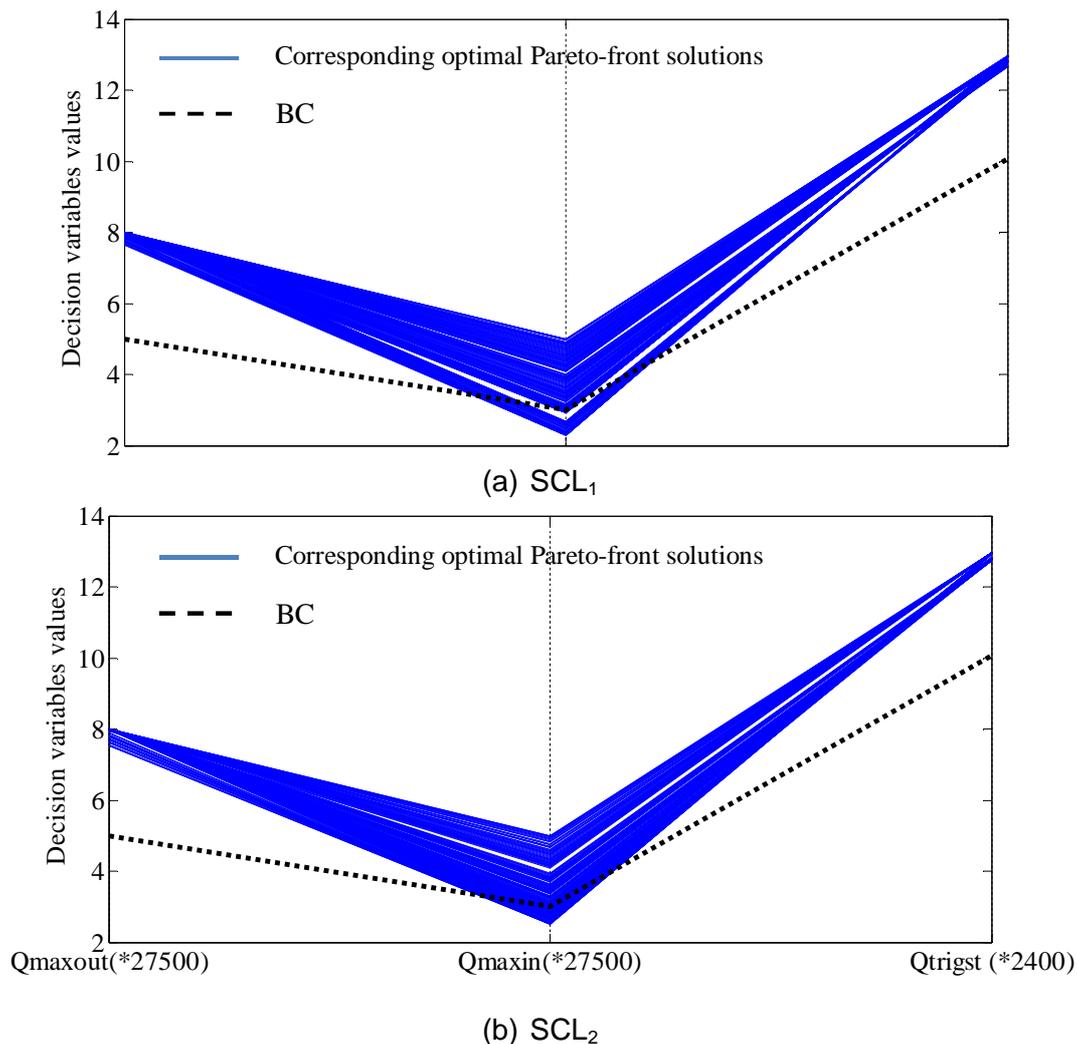


Figure 5.11 Operational control parameters of the all optimal solutions in SCL₁ and SCL₂

In order to further illustrate the impact of each scenario's optimal operational control on the water quality parameters (optimisation objectives) in the river, several operational control strategies are selected from the *compliant region* for each scenario.

Three operational control strategies: A₂, B₂ and C₂ are selected from the optimal Pareto-fronts for SCA and the two climate change scenarios; SCB and SCC. The DO and AMM concentrations in reach 40 and 10 of the river for these selected solutions are presented in Figure 5.12 and Figure 5.13. The increased min DO concentrations and reduced max AMM concentrations in these two figures illustrate the general observation previously made in terms of improving the quality of water by optimising the operational control of the IUWS under the climate change (see also Figure 5.6).

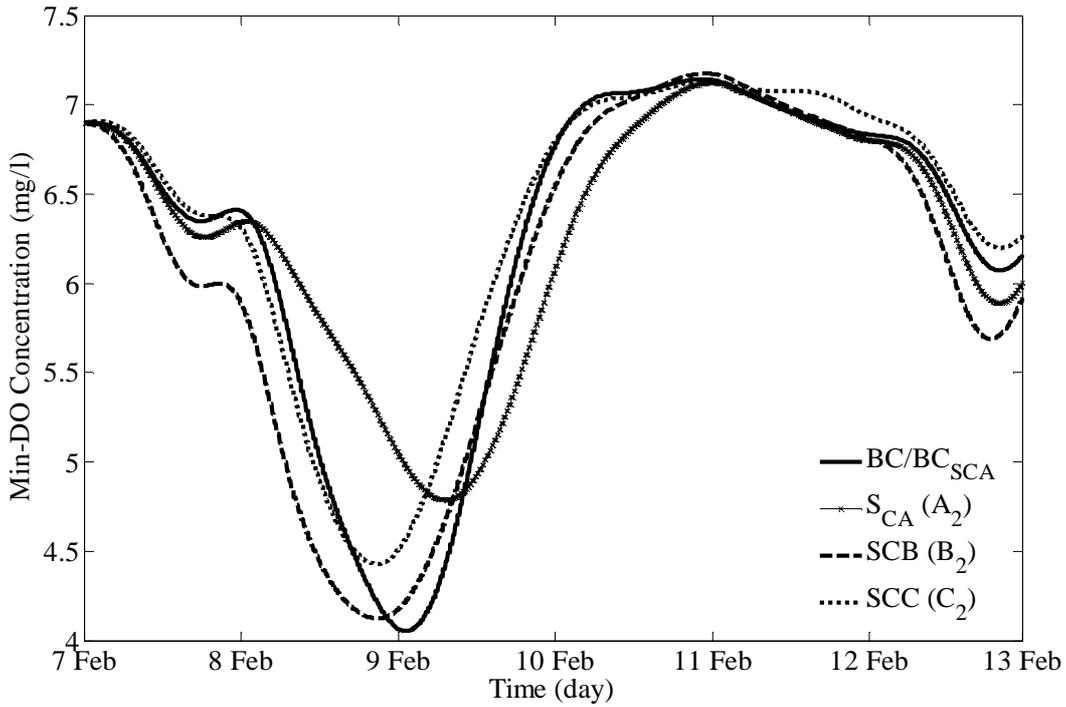


Figure 5.12 Min-DO concentration in reach 40 of the river

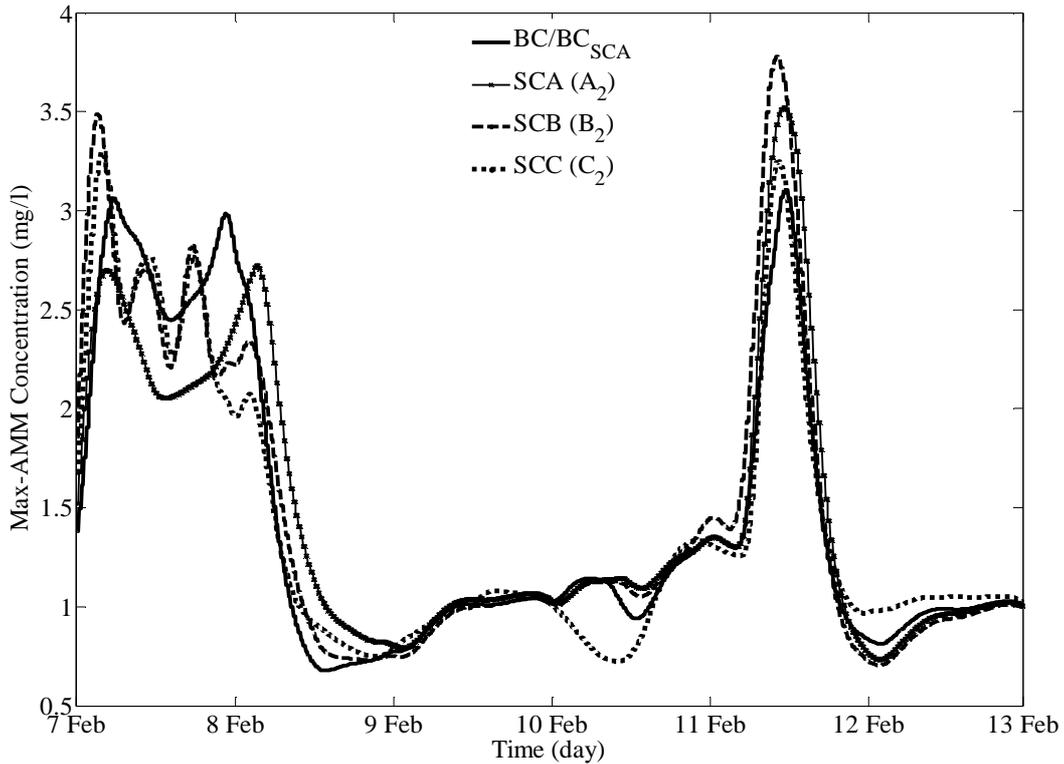


Figure 5.13 Max-AMM concentration in reach 10 of the river

Opposite of that, in scenarios SCL₁ and SCL₂ which consider combined effect of climate change and urbanisation growth, all operational control strategies are leading to worsening water quality in the river, as shown in Figure 5.14 and Figure 5.15. These two figures show min DO and max AMM concentrations for two operational control strategies (L₂₂, L₁₂) which are selected from the middle of corresponding SCL₁ and SCL₂ Pareto optimal fronts, thus representing a

good trade-off between the two competing objectives. As it can be observed from these two figures, the obtained min DO and max AMM concentrations are far from the 4 mg/l standard (dashed line) which shows the significant worsening of water quality under these two scenarios.

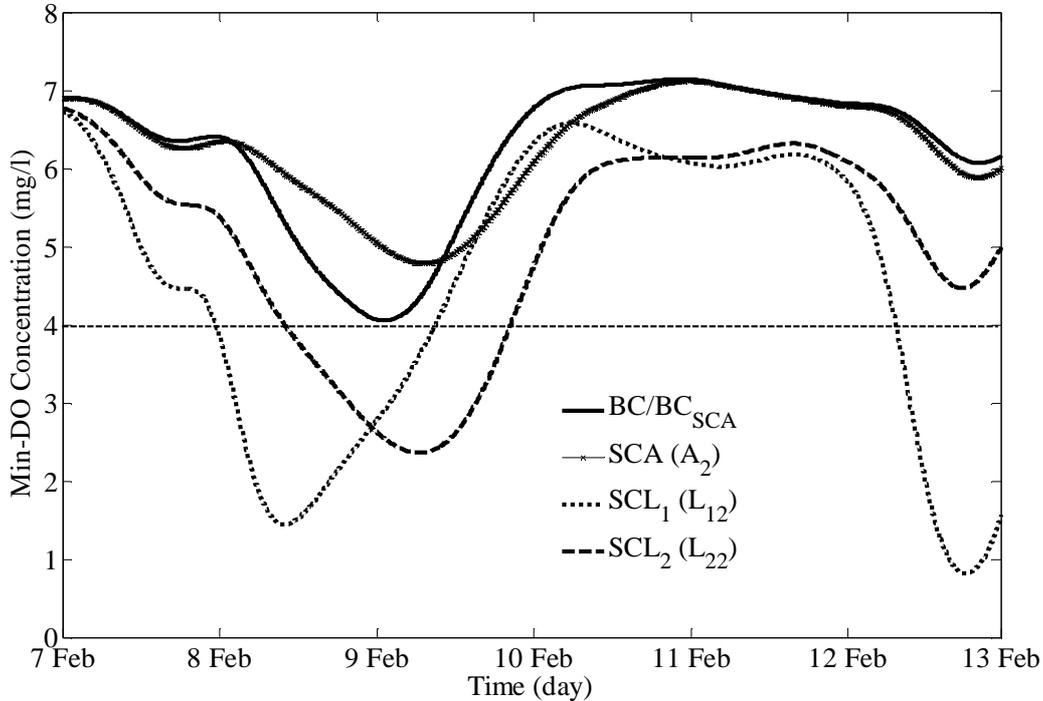


Figure 5.14 Min-DO concentration in reach 40 of the river

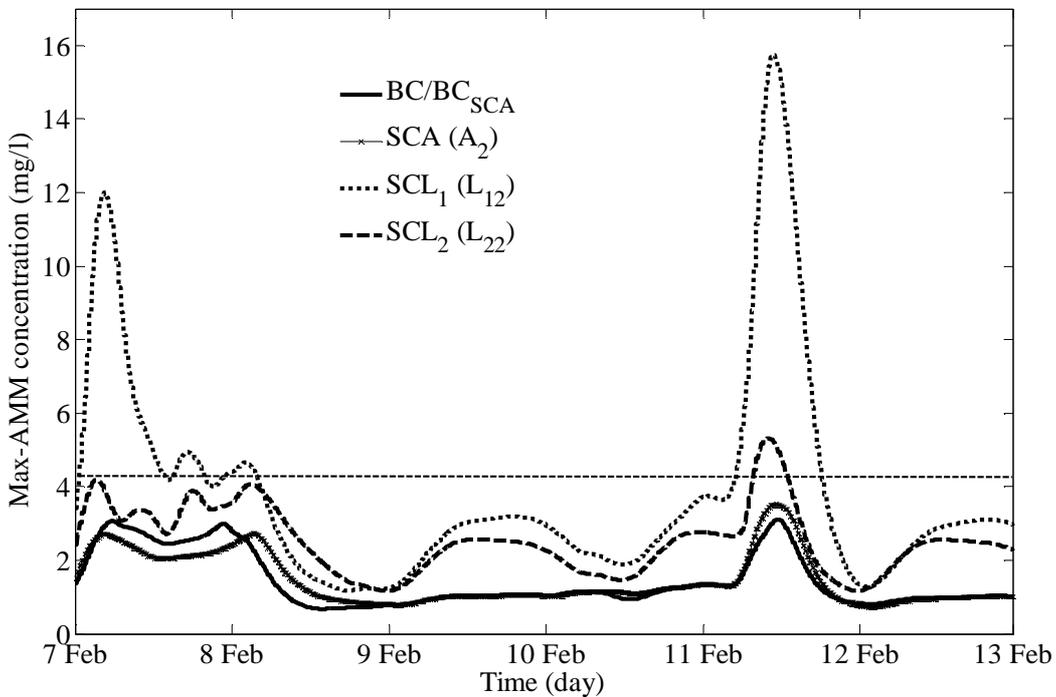


Figure 5.15 Max-AMM concentration in reach 10 of the river

5.4.3.2 Comparison of Water Quality Before and After Operational Control Optimisation

To further observe the effectiveness of IUWS operational control optimisation to improve the water quality under the future climate change and urbanisation growth, it is necessary to compare the water quality indicators before and after the optimisation. For the purpose of comparison, DO and AMM concentrations are presented in Figure 5.16, Figure 5.17, Figure 5.18 and Figure 5.19 before and after the operational control optimisation in reach 40 and 10 of the river. Two representative scenarios which are the worst cases (with regard to their impacts on the water quality parameters in Figure 5.6 and Figure 5.8) among the climate change scenarios and combined climate change with urbanisation scenarios are selected. Therefore for this purpose SCL_1 and SCB are selected.

In the first step the IUWS input parameters are set according to SCB and SCL_1 (see Table 5.1) and without doing any operational control optimisation. Then DO and AMM concentrations are evaluated at reach 40 and 10 of the river respectively (line curves in Figure 5.16, Figure 5.17, Figure 5.18 and Figure 5.19). Subsequently those two representative solutions B_2 and L_{12} (shown in Figure 5.6 and Figure 5.8) are selected to represent the DO and AMM concentrations at reach 40 and 10 after the operational control optimisation (dashed curves).

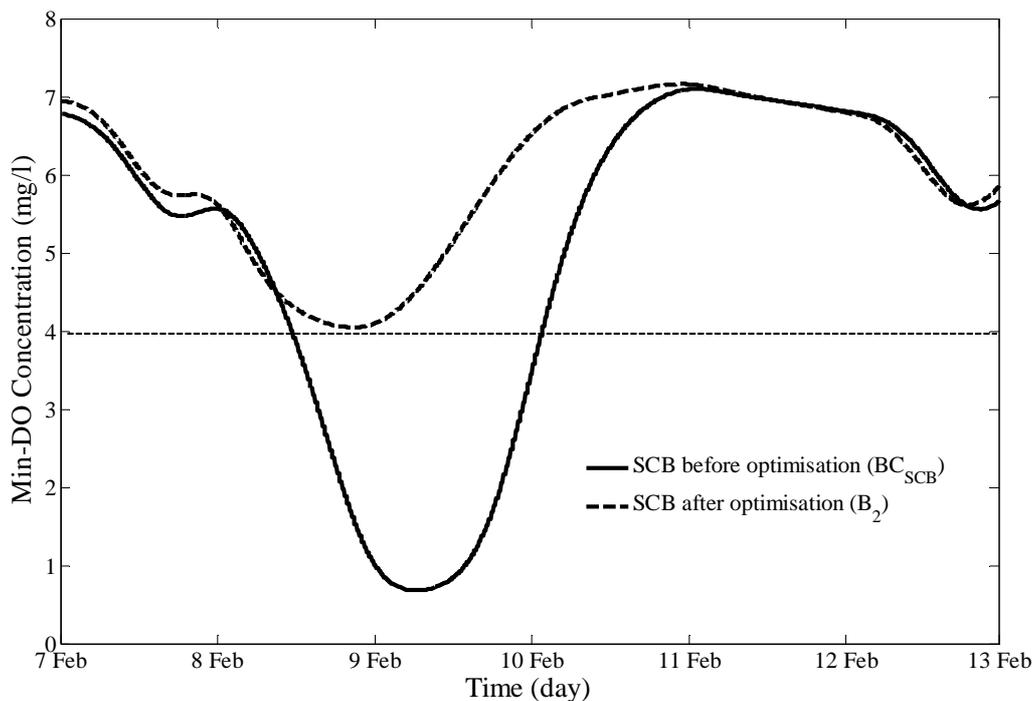


Figure 5.16 Min-DO concentration before and after the optimisation in the reach 40 of the river in SCB

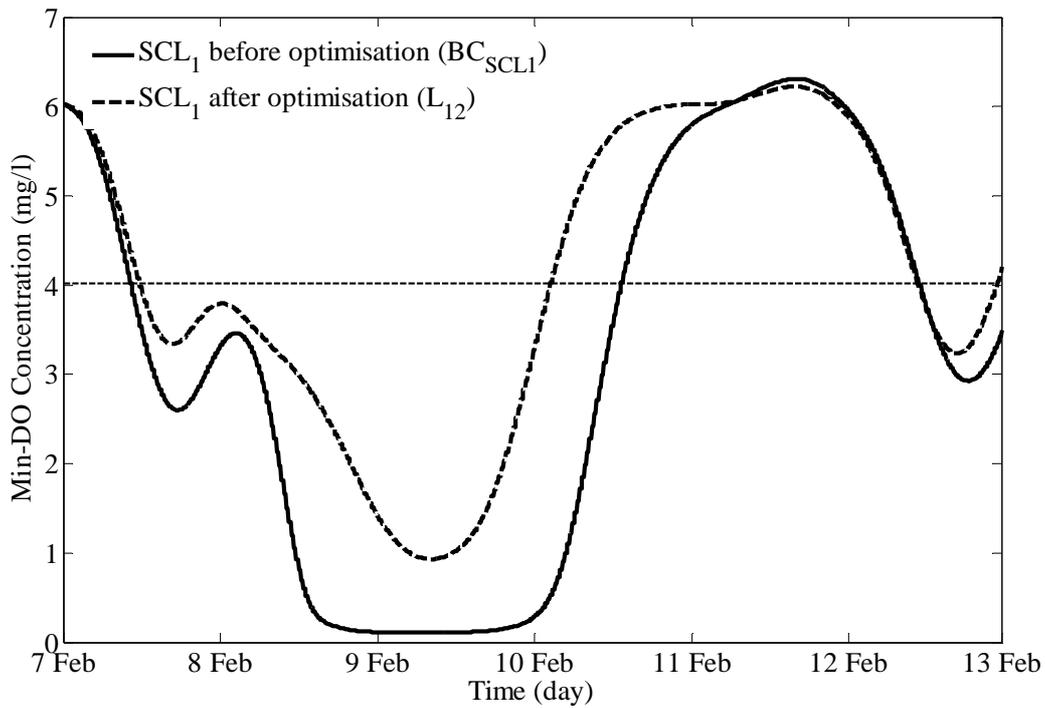


Figure 5.17 Min-DO concentration before and after the optimisation in the reach 40 of the river in SCL₁

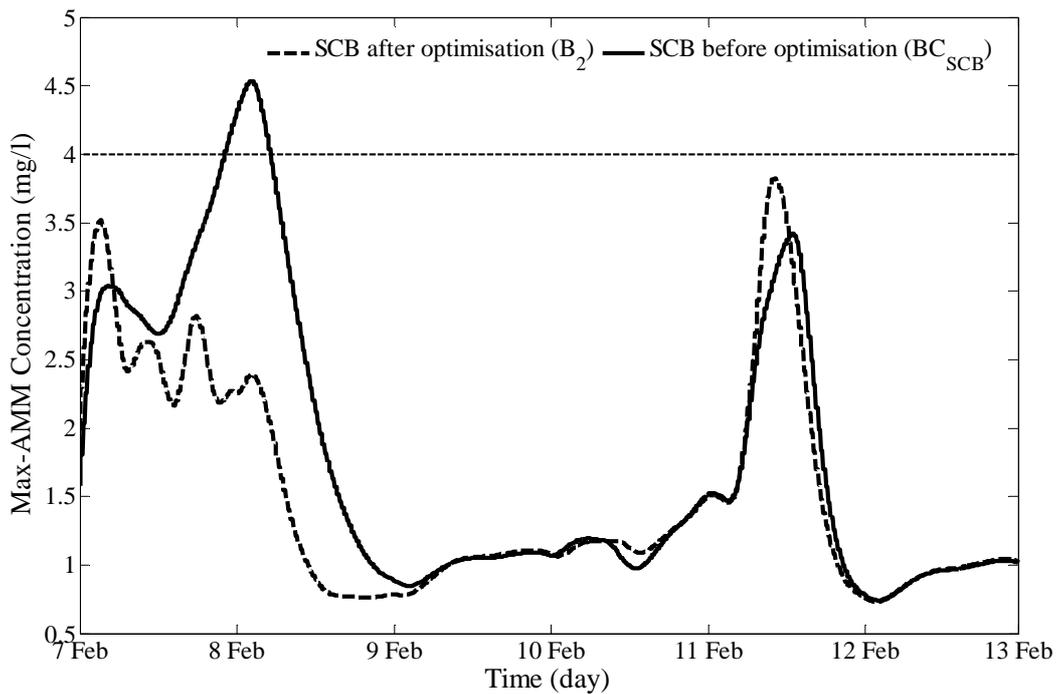


Figure 5.18 Max-AMM concentrations before and after the optimisation in reach 10 of the river in SCB

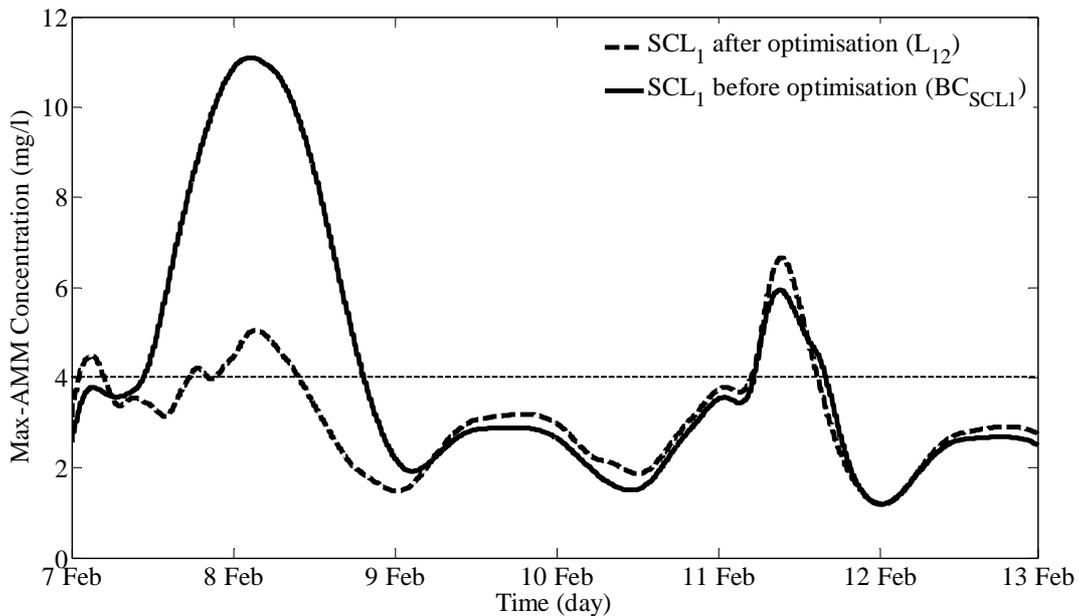


Figure 5.19 Max-AMM concentrations before and after the optimisation in reach 10 of the river in SCL₁

Figure 5.18 shows that before doing any operational control optimisation in SCB, min DO concentration fails to reach the 4 mg/l standard but after implementing the operational control optimisation, the optimal operational control strategy B_2 (which is within the *compliant region* shown in Figure 5.6), is improved and satisfies this standard. The same result can be observed for the max AMM concentration in B_2 before and after the operational control optimisation.

Figure 5.18 also shows the AMM concentration can meet the standard after operational control optimisation. Therefore it can be concluded that under the climate change scenarios considered in this study, the operational control optimisation of the IUWS has been effective to satisfy the quality of water in the rivers. Also in SCL₁ similar to SCB, the operational control optimisation has the potential to improve the DO and AMM concentrations (Figure 5.17 and Figure 5.19) in some extents but is not enough to satisfy the water quality criteria.

As a result the operational control optimisation of the IUWS has the potential to improve the water quality indicators in the river under the future changes but it is limited to some scenarios. In other words for the defined climate change scenarios in this study, the operational control optimisation has been able to improve the quality of water to the standard required. However, the same cannot be said for the combined climate change and urbanisation scenarios.

Therefore alternative strategies for these scenarios are required to improve the quality of water such as rehabilitation, redesign of the IUWS or similar.

5.5 Summary

In this chapter, an attempt to reduce the negative impact of climate change and urbanisation on the water quality in the river was made by optimising (i.e. improving) the operational control of the IUWS and the extent of the effectiveness of this strategy were presented.

With regard to the potential of future climate change, the results presented in this chapter illustrate that the operational control optimisation has the potential to improve the quality of water under the considered climate change scenarios. This improvement seems more effective in the case of increased RI (SCC) than in the case of increased RD (SCB) as the increased volume of rainfall has a more negative impact on the water quality in the river. In addition to this, the results obtained showed that the values of the urbanisation parameters (specifically PCW as the most sensitive urbanisation parameter in terms of impact on the river water quality) are effective factors on the quality of water.

The target water quality in the river seems also achievable by optimised operational control when climate change is combined with minimum urbanisation growth (scenarios SCK₁ and SCK₂). The results for these two scenarios show that reduced PCW in these cases helps meeting the water quality criteria. However, the target water quality in the river is not achievable when climate change is combined with maximum urbanisation growth (scenarios SCL₁ and SCL₂). In this case, optimal operational control on its own cannot improve the quality of water in the river and alternative approach involving IUWS redesign/rehabilitation is necessary to improve the system performance.

The next chapter aims to resolve the above problem, i.e. aims to improve the system performance by re-designing the IUWS.

CHAPTER 6

IMPROVED INTEGRATED URBAN WASTEWATER SYSTEM DESIGN

6.1. Introduction

The IUWS operational optimisation results obtained in the previous chapter under assumed climate change and urbanisation demonstrated clearly that optimised operational control of the IUWS under these conditions cannot improve the water quality in the recipient to a level which makes it compliant with current regulations. This indicates that the IUWS is likely to require other modification such as redesign or rehabilitation of the sewer network and/or wastewater treatment works. This chapter aims to improve the IUWS performance by increasing the catchment wastewater storage capacity. In section 6.2 the optimisation model is formulated and applied to the critical scenarios. The results are discussed in section 6.3, and a summary of findings are presented in the last section.

6.2. IUWS (Re)Design Problem

6.2.1. Introduction

Chen *et al.* (2004), Butler & Davies (2011) and Even *et al.* (2007) noted that CSOs deteriorate the quality of water in the rivers. Storage tanks are common structural measures used to limit CSO discharges in combined sewer systems, although several other management options are available to reduce the input wastewater, including reducing surface runoff, DWF to the system. A well-established method is to consider additional storage for upgrading the system to cope with the excess wastewater generated from, for example, future urban development (Lau, *et al.*, 2002). These storage enhancements are important in

reducing the negative impacts of future changes such as climate changes and/or urbanisation growth, as Butler *et al.* (2007) have shown for a case study in London.

Storage tanks provide a volume for the temporary storage of combined wastewater and storm water during a rainfall event, and the stored water can be released back into the urban wastewater system gradually. Butler & Davies (2011) introduced the primary functions of the storage system in attenuating flow, limiting localised flooding and reducing the volume of polluted storm water discharges into the river. Lau *et al.* (2002) showed that the minimisation of CSO discharge volume/frequency does not necessarily lead to improved water quality in the receiving waters. Fu *et al.* (2010) investigated the optimal distribution and operational control of the storage tanks with an objective to mitigate the impact of new residential development on receiving water quality from an integrated modelling perspective. They considered two receiving water quality indicators and the cost of storage tank construction as the optimisation model objectives.

The IUWS (re)design problem is formulated here as an optimisation problem and solved using the MOGA-ANN β algorithm described in the previous chapter (see section 5.3).

6.2.2. Problem Definition

The case study used in Chapter 5 is also used here. The IUWS schematic shown earlier (Figure 3.2) was updated by adding the potential storage tank locations, as shown in Figure 6.1.

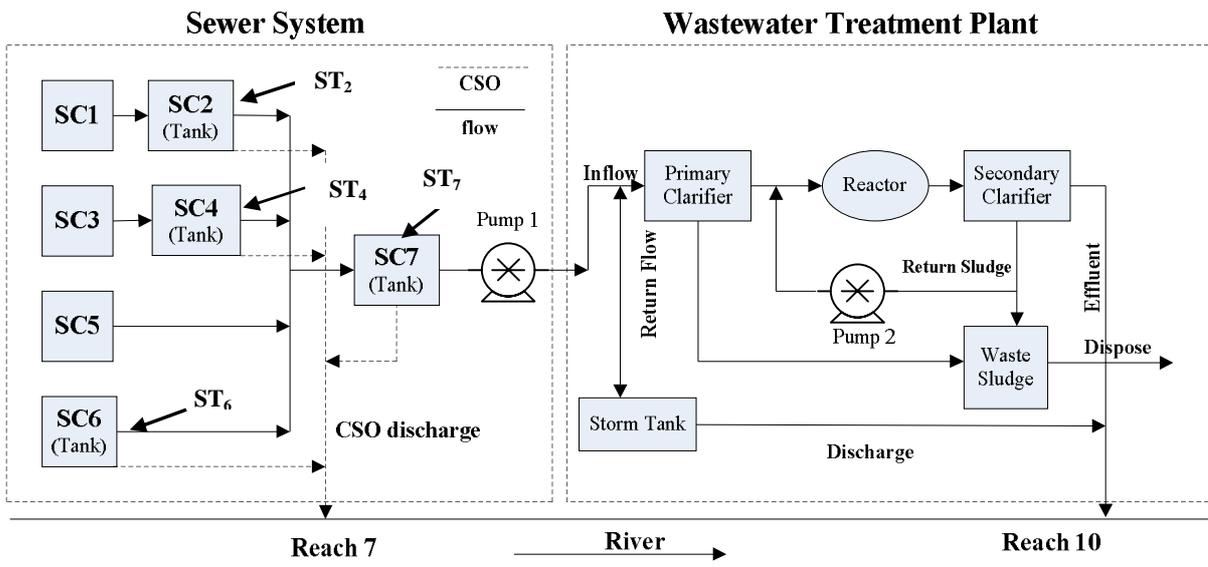


Figure 6.1 Updated schematic of the analysed IUWS

Figure 6.2 shows the iterative procedure of the design optimisation process to find the aforementioned wastewater storage capacity increase required in this chapter. This iterative procedure is comprised of the following steps:

1. Assume the system storage capacity increment (c).

The factor c is the percentage storage capacity increment-coefficient applied to the existing storage capacity of the catchment to increase it. Therefore the upgraded storage capacity of the catchment is estimated by equation (6.1).

$$V_{new} = V(1 + c/100) \quad (6.1)$$

where, V_{new} : increased storage capacity of the catchment (m^3); V : current storage capacity of the whole catchment equal to $13,200 m^3$.

As the operational control optimisation in SCB and especially in SCL_1 and SCL_2 could not meet the *compliant region* in Chapter 5, the IUWS under these scenarios is upgraded in this chapter (These scenarios are named critical scenarios in this chapter).

The objectives of the IUWS design optimisation problem are the same as the objectives described in Chapter 5 (section 5.2.1).

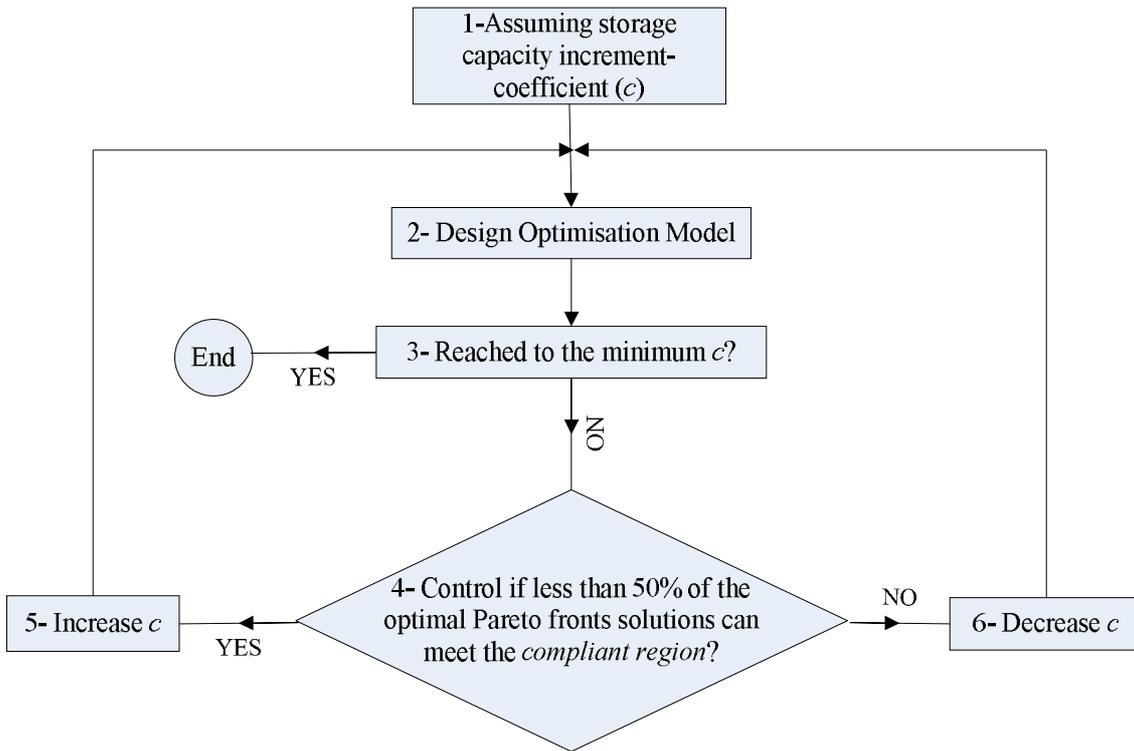


Figure 6.2 Schematic diagram of the iterative procedure to determine the minimum c

In the design optimisation model in addition to the operational control parameters, design parameters are added as shown in Table 6.1.

The V_{new} obtained (see step 1), has to be distributed among the existing storage tanks (ST_2 , ST_4 , ST_6 and ST_7 in Figure 6.1) in the sewer system. The relevant storage tanks contribution- coefficients are introduced here and used as decision variables. The storage tank contribution coefficient is defined as the following:

Storage tank contribution-coefficient (a_i)

The storage capacity increased 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 equation (6.2):

$$ST_i = V_i + V_{new} \times a_i/100 \tag{6.2}$$

$$\sum a_i/100 = 1$$

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 6.1).

2. Apply c to the design optimisation model.
3. Control whether the minimum c was achieved or not. To ensure about this, it is required to increase/decrease the c (see the next steps) until reaching the 50% target (see the next step for definition of the 50% target). If the minimum c was achieved, the algorithm is finished and if not the increase(s)/decrease(s) will be continued until reaching this target.
4. Control whether most of the optimal Pareto-front solutions (most meaning 50% in this study) fit into the *compliant region*. The reason for this is that, apart from the water quality impact, cost is an important factor that affects the decisions to upgrade the system. Fu *et al.* (2010) considered the system design cost as an optimisation objective that had to be minimised.

In this study a surrogate of budget approach is applied leading to limit the redesign cost by finding the minimum c required to improve the system performance. This can provide more options for the decision makers to improve the system performance. The redesign costs estimated through this way have the potential to demonstrate the minimum redesign budget needed to improve the system performance while coping with the future changes.

The above said value 50% was achieved with several tests on the design optimisation model and investigating its behaviour in terms of the redesign cost and the number of solutions within the *compliant region*. As aforesaid,

the more possible number of solutions within the *compliant region*, the better support for the decision makers and future planners is provided. The abovementioned tests showed that when the threshold values of more than 50% (e.g. 60% or above) were considered, the obtained optimal Pareto-front could meet the *compliant region* completely. This is good in terms of meeting the water quality criteria but at the same time c increased significantly and this increases the redesign cost which is not desirable. In another side when the threshold values less than 50% were considered, a different behaviour from the design optimisation model was observed. In this case a few solutions (similar to Fu *et al.* (2010)) could meet the *compliant region* so the numbers of solutions within the *compliant region* were not satisfactory while the c value decreases and this is desirable. All these tests led to adopting the average value of 50% as a reasonable value in this study which can satisfy both decision makers' preferences in terms of the number of solutions and the c value to limit the redesign cost.

5. If less than 50% of the optimal Pareto-front solutions are within the *compliant region*, increase the value of c and return to step 2. This increase range is variable and depends on how far the optimal Pareto-front is from the *compliant region*. If it is completely out of the *compliant region*, the increase step is between 50-100 % but if it is within the *compliant region*, the increase step is between 5-20%.
6. If, however, more than 50% of the optimal Pareto-front solutions were within the *compliant region*, decrease the value of c until reaching the 50% target.

The minimum value of c obtained from the above steps is used to calculate the associated IUWS redesign costs.

The above costs are comprised of the construction and operating costs. Construction costs can be estimated by use of cost functions of tank volumes or area in the form of power laws or polynomials. The operating costs are neglected in this study as the initial tests showed that the difference between the maximum operating cost value (i.e. in the optimal Pareto-front solutions) and the minimum one is very low. The detailed formation of a cost function may vary significantly in different times, regions, or countries (Fu, *et al.*, 2010).

Storage capacity costs are estimated after Gillot *et al.* (1999):

$$C = \sum_i 5559 ST_i^{0.473} \quad (6.3)$$

where,

C : total cost of the system upgrade (*Euro*) ;

ST_i : volume of i^{th} storage tank (m^3).

Table 6.1 Decision variables of the IUWS design optimisation model

	Decision variable(units)	Decision variable description	Values and value ranges used in operational control optimisation	Value ranges used in (re)design optimisation
Design parameters	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]
Operational control parameters	Q_{ST2} (m^3/d)	The maximum outflow rate of ST_2	5xDWF*	[2xDWF,9xDWF] *
	Q_{ST4} (m^3/d)	The maximum outflow rate of ST_4	5xDWF*	[2xDWF,9xDWF] *
	Q_{ST6} (m^3/d)	The maximum outflow rate of ST_6	5xDWF *	[2xDWF,9xDWF]*
	Q_{maxout} (Q_{ST7}) (m^3/d)	The maximum outflow rate of sewer system (ST_7)	[3xDWF,8xDWF] **	[2xDWF,9xDWF]**
	Q_{maxin} (m^3/d)	The maximum inflow rate to the WWTP	[2xDWF,5xDWF]**	[2xDWF,5xDWF]**
	Q_{trigst} (m^3/d)	The threshold triggering emptying the storm tank	[16416,31104]	[16416,31104]

*These values are multiplied in the DWF value of their relevant sub-catchment area (see Figure 6.1)

**These values are multiples of the treatment capacity of the WWTP (27,500 m^3)

6.3. Optimisation Results and Discussion

6.3.1. Pareto- fronts

The design optimisation was applied for the critical scenarios i.e. SCB, SCL_1 and SCL_2 (see section 6.2.2). Figure 6.3, Figure 6.4 and Figure 6.5 show the Pareto-fronts representing optimal trade-off minimum DO and maximum AMM concentrations for the aforementioned scenarios. In addition to the Pareto-fronts of the design model, the Pareto-fronts of the operational control model are demonstrated for comparisons in the aforementioned figures. Also the BC_{SCB}

point (see Figure 5.6), BC_{SCL_1} (see Figure 5.8) and BC_{SCL_2} (see Figure 5.8) showing the performance of the IUWS under SCB, SCL_1 and SCL_2 are presented in Figure 6.3, Figure 6.4 and Figure 6.5 respectively.

Table 6.2 shows the minimum c , the least additional storage capacity and the minimum redesign cost (C) required in SCB, SCL_1 and SCL_2 that more than 50% of their associated optimal Pareto-fronts can meet the *compliant region*.

Table 6.2 Cost of IUWS upgrades for different scenarios

Scenario	Minimum c (%)	Additional storage capacity in the catchment (m^3)	C (Euro)
SCB	100	13,200	494,340
SCL_1	675	89,100	1,219,800
SCL_2	500	66,000	1,058,400

Using the iterative procedure, it was found that about 100%, 675% and 500% storage capacity increases are required in SCB, SCL_1 and SCL_2 respectively, in order to meet the bounds of the *compliant region*. The aforementioned system upgrades, add 13,200 m^3 , 89,100 m^3 and 66,000 m^3 additional storage capacities to the current storage capacity of the system (13,200 m^3). Also to cope with the future changes in SCB, SCL_1 and SCL_2 requires about € 494,340, € 1,219,800 and € 1,058,400 investment for upgrading the system to meet the *compliant region*.

As it can be observed in the aforesaid figures the Pareto-fronts achieved in Chapter 5 by the operational control optimisation (see crosses in Figure 6.3, Figure 6.4 and Figure 6.5) are dominated by the solutions obtained from the IUWS design optimisation and the BC_{SCB} , BC_{SCL_1} and BC_{SCL_2} points are dominated by both operational control and design optimal Pareto-fronts.

This indicates that the changes exerted in the operational control parameters (see Table 6.1) and increments of the catchment storage capacity (see Table 6.2), has had enough potential to improve the system performance so that more than 50% of the optimal Pareto-fronts' solutions can meet the *compliant region* in SCB, SCL_1 and SCL_2 . These significant improvements, in the performance of the system, can highlight the importance of upgrading the existing IUWS to deal with the proposed future changes especially under the combined scenarios in the future (i.e. SCL_1 and SCL_2). For instance SCL_1 as the most critical scenario

(see Figure 6.4) needs the maximum storage capacity increase and consequently the maximum redesign budget to cope with the future changes.

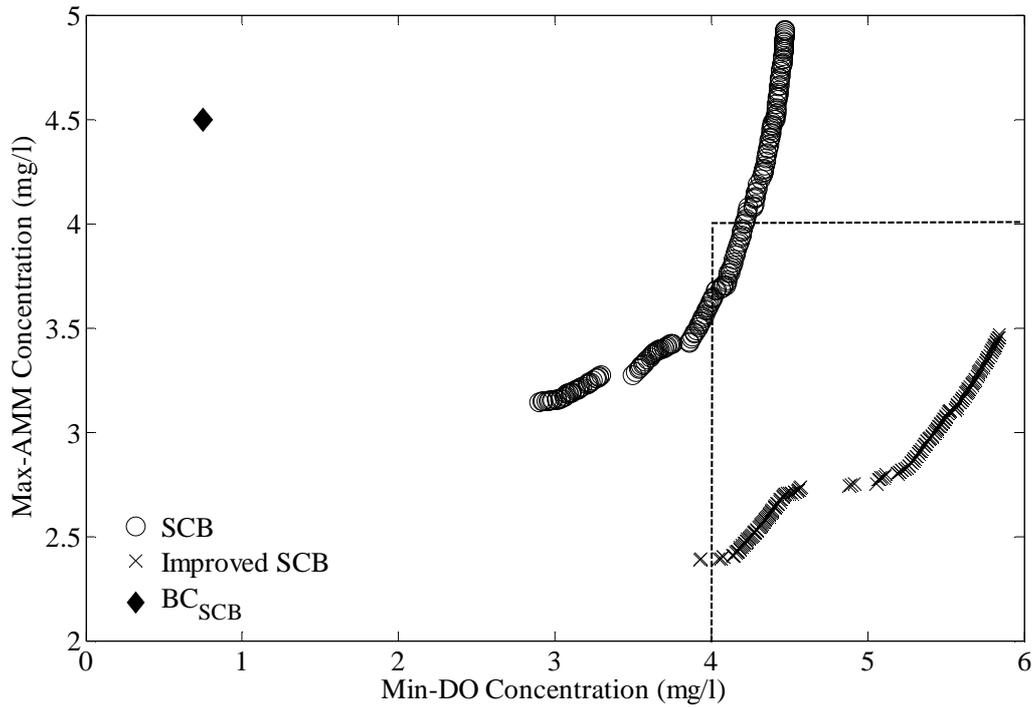


Figure 6.3 Optimal Pareto-fronts obtained for SCB from the design optimisation model

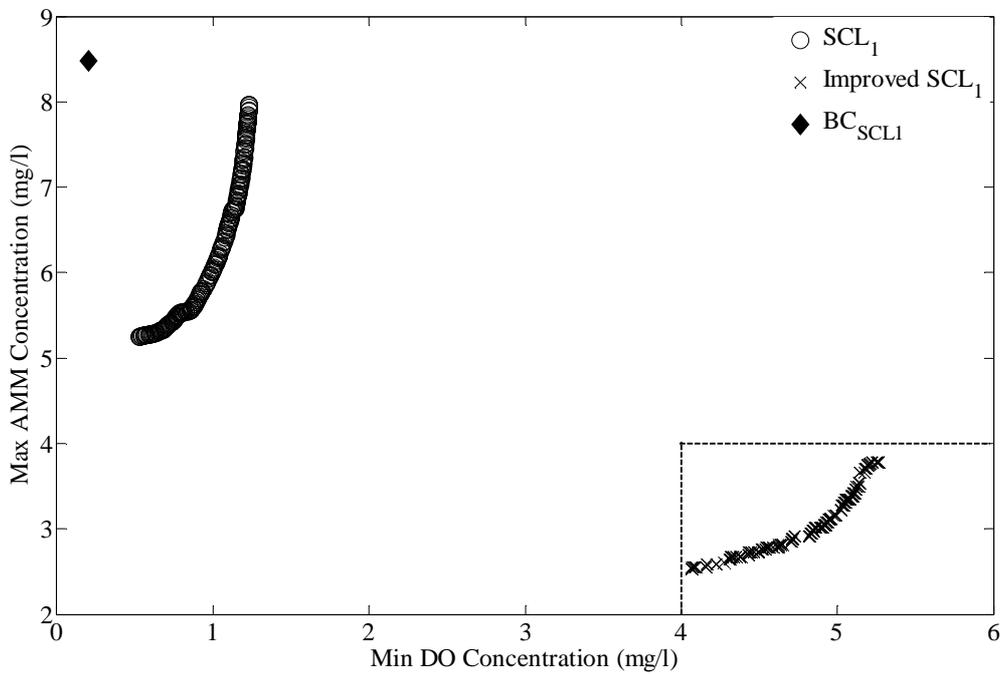


Figure 6.4 Optimal Pareto-fronts obtained for SCL₁ from the design optimisation model

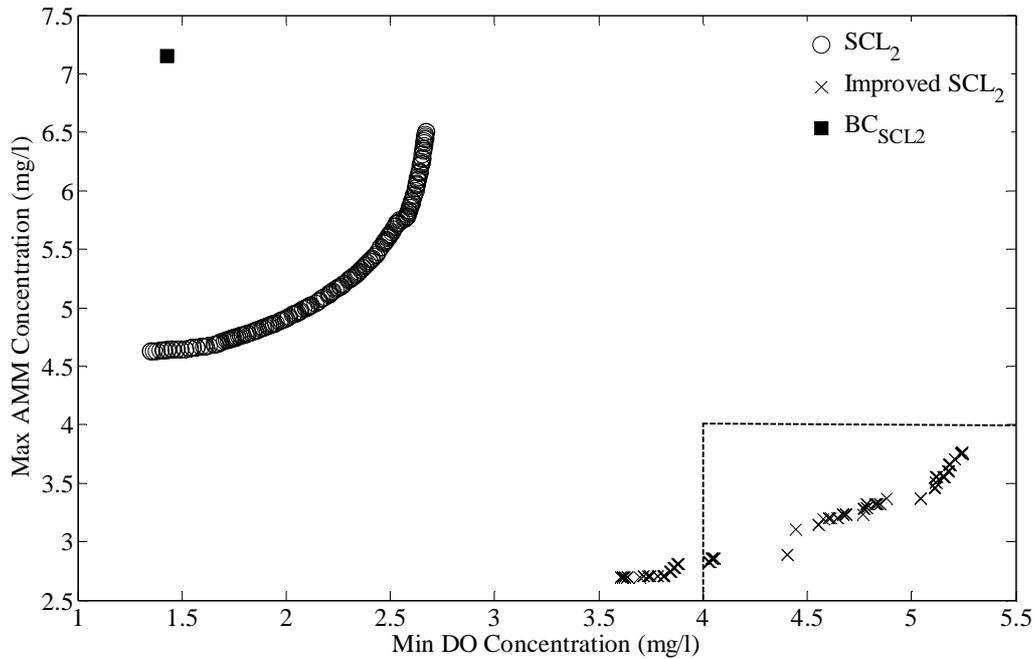


Figure 6.5 Optimal Pareto-fronts obtained in SCL_2 from the design optimisation model

With regard to the achieved optimal Pareto-fronts for all the scenarios, it is important to look into the details of the individual solutions obtained, i.e. the optimised operational control and design parameters' values shown in Table 6.1. When doing so, all the solutions within the *compliant region* are selected as they are likely to be selected by any decision maker.

6.3.2. Comparison of Solutions Obtained in Operational Control and Design Optimisation Models

Figure 6.6 displays the values of the design parameter a (see Table 6.1) for all the optimal solutions within the *compliant region* in scenarios SCB, SCL_1 and SCL_2 . Note that the horizontal axis shows the design parameters and the vertical axis shows their corresponding values. The dashed lines show the values of a in the BC. The lines with the descending and ascending slopes show the decreases or increases of the role of the storage tanks to meet the *compliant region* which arisen from the existing interactions among the storage tanks. The following observations can be obtained from Figure 6.6 for the design parameters.

For SCB, it can be observed in Figure 6.6a that a_7 (see Table 6.1 and relevant to ST_7 in Figure 6.1) decreased compared to its value in the BC. This shows that the storage capacity of ST_7 (see Figure 6.1) has been overdesigned for

SCB and has the potential to be reduced in the design optimisation model to meet the *compliant region*. The a_7 in SCL_1 and SCL_2 (Figure 6.6b and Figure 6.6c) nearly needs to be doubled (comparing to the BC) till the optimal Pareto-front can meet the *compliant region*. This shows that the current volume of ST_7 is not large enough in SCL_1 and SCL_2 to cope with the future changes.

In Figure 6.6a, a_2 , a_4 and a_6 (see Table 6.1) almost increased for majority of the strategies for SCB comparing to the BC. This indicates that the current storage capacity of ST_2 , ST_4 and ST_6 was not enough to fully meet the *compliant region*. In other words increasing the storage capacity of the catchment about 100 % has the potential that more than 50% of the optimal Pareto-front solutions can meet the *compliant region* in SCB. For SCL_1 and SCL_2 in Figure 6.6b and Figure 6.6c, it can be observed that a_2 , a_4 and a_6 decreased comparing to the BC. This indicates that even with 675 % and 500 % storage capacity increases in SCL_1 and SCL_2 , a_2 , a_4 and a_6 were decreased. In other words the current storage capacities of these tanks are too large, i.e. these tanks are over dimensioned. Therefore the design optimisation can optimally reduce the unnecessary storage capacities and consequently the investment budget under the future changes to meet the *compliant region*.

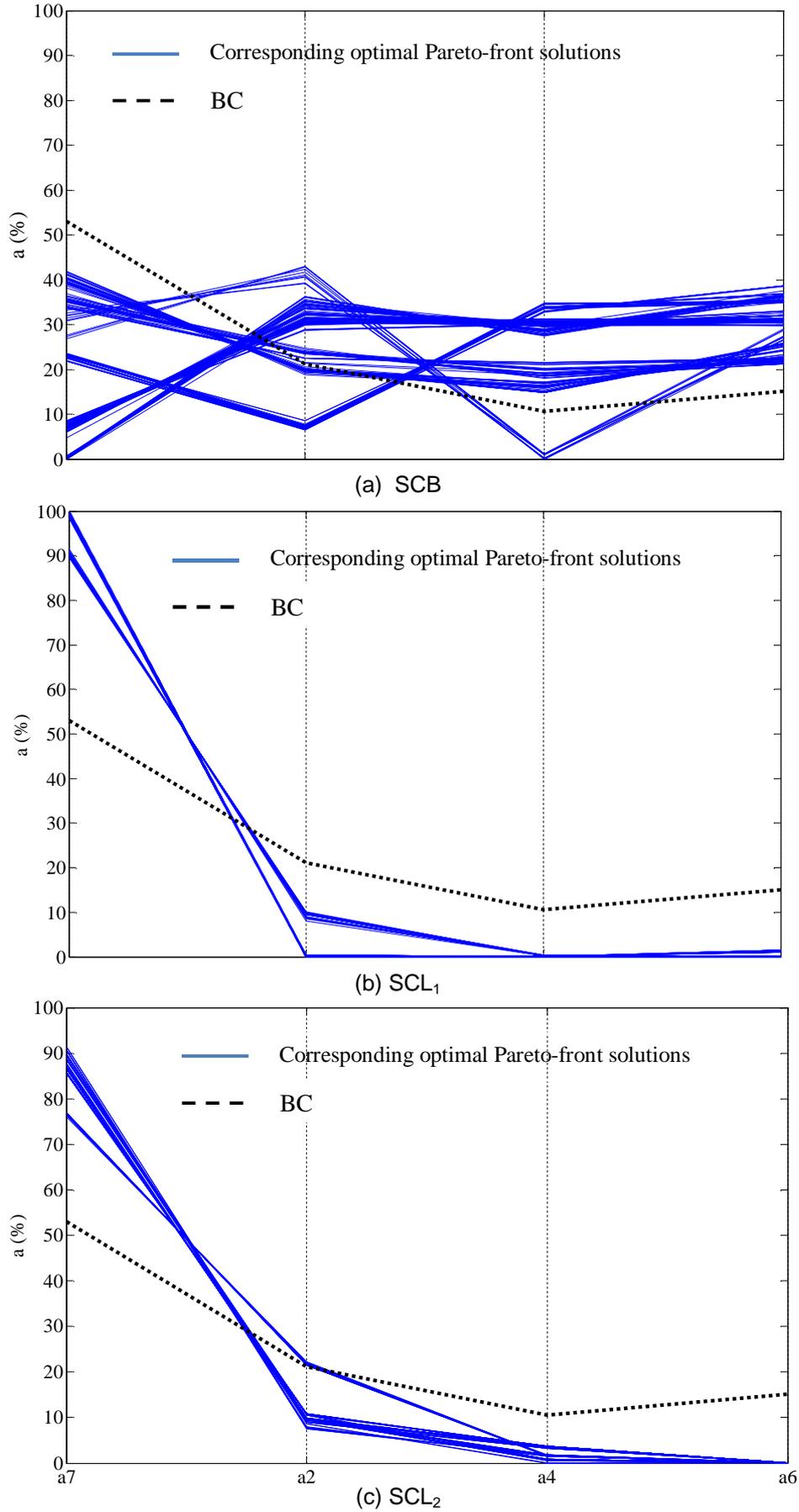


Figure 6.6 The parameter a in SCB, SCL₁ and SCL₂

Figure 6.7a, Figure 6.7b and Figure 6.7c show the IUWS operational control parameters for all the optimal solutions within the *compliant region* in SCB, SCL₁ and SCL₂ (see Figure 6.3, Figure 6.4 and Figure 6.5) respectively. The dashed lines on these figures show the nominal values of the maximum outflow rates presented in Table 6.1. The slopes between the operational control parameters, can be expressed the same as section 5.4.3.1.

Generally it can be observed from Figure 6.7a, Figure 6.7b and Figure 6.7c that, $Q_{\max\text{out}}$ obtained from the design optimisation model, nearly have decreased significantly in all the scenarios comparing to the BC (dashed line). These decreases are prompted by the ST₇ to use efficiently the increased storage capacities and storing more wastewater generated to partially treat them. The same thing can be observed about $Q_{\text{ST}2}$ in the ST₂.

Meanwhile $Q_{\text{ST}4}$ and $Q_{\text{ST}6}$ in SCL₁ or $Q_{\text{ST}6}$ in SCL₂ increased comparing to the BC (dashed line). These increases are arisen from the system to discharge more wastewater from the system to reduce the CSOs and hence meet the *compliant region*.

$Q_{\max\text{in}}$ and Q_{trigst} do not show significant variation to the dashed line in SCB and SCL₁ as the WWTP capacity has not changed while variations can be observed under RI in SCL₂ that system intends to deal with more wastewater treatment work to cope with the future changes.

The aforementioned observations in Figure 6.7a, Figure 6.7b and Figure 6.7c indicate that under the future climate change and urbanisation, improving the design of the system may completely change the behaviour of the system through the existing interactions between the parameters (i.e. operational control and design) aiming to meet the *compliant region*.

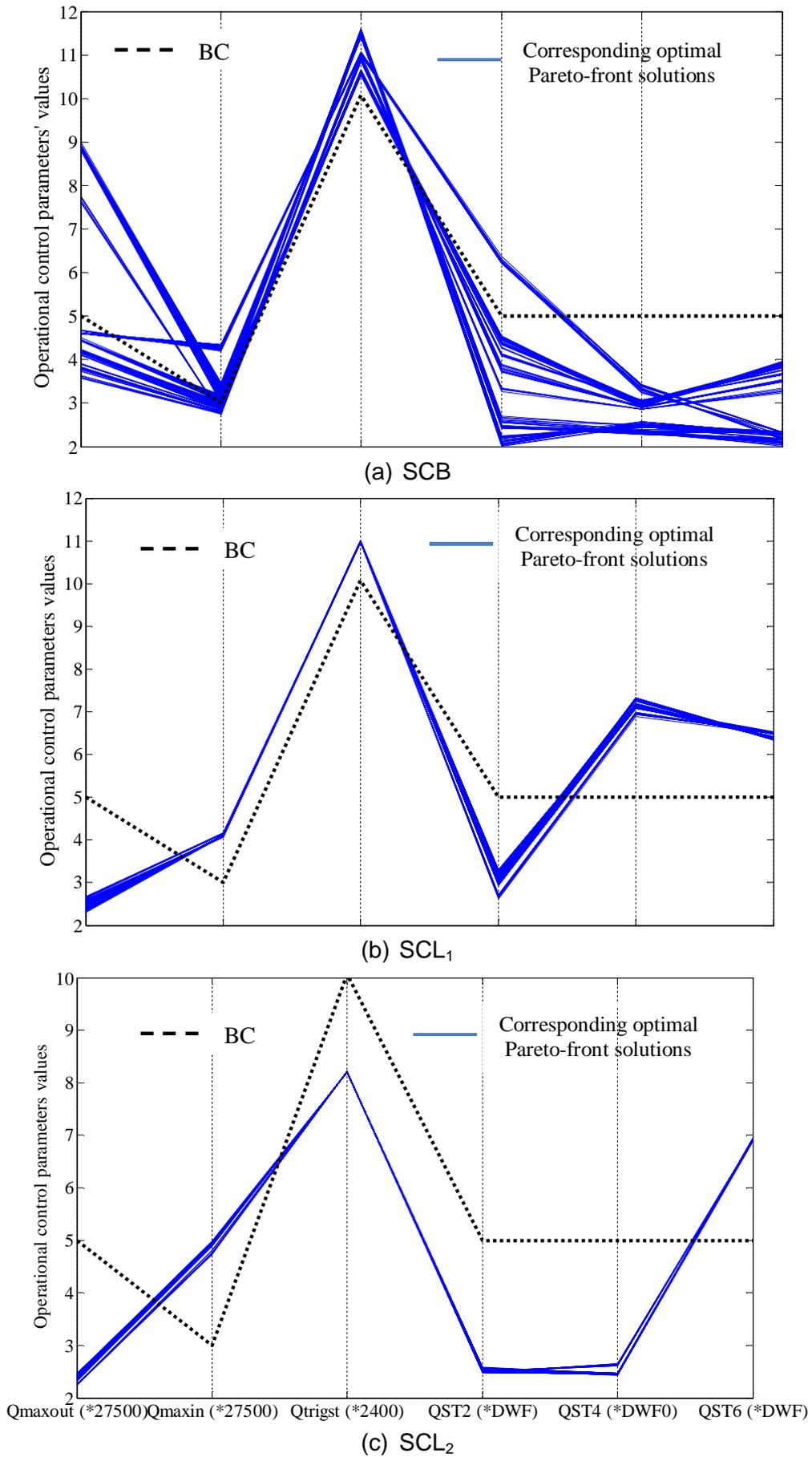


Figure 6.7 IUWS operational control parameters in SCB, SCL₁ and SCL₂

6.4. Summary

In this chapter the IUWS performance was improved by upgrading the storage capacity of the catchment in the critical scenarios of Chapter 5 and also by modifying the operational control strategy of the IUWS. These improvements were performed by changing the operational control and redesign of the system storage capacity. Cost and water quality were two criteria used to evaluate the system performance.

As a result, this chapter has shown that for improving the IUWS performance in order to cope with the future climate and urbanisation changes, redesigning (in addition to the operational control) of the system may be required. This is required to meet both economic and water quality criteria, under the examined climate change and urbanisation scenarios.

The analysis carried out in this chapter and the corresponding results obtained indicate the importance of considering sewer and WWTP systems as integrated systems as this enables observing and quantifying the interactions between their components. All this, in turn, then enables dimensioning each IUWS component adequately so that the system as a whole can deliver the best/target performance.

The results obtained also demonstrated that considering the combined impact of climate change and urbanisation for the system performance improvement, increases costs over just climate change impacts.

Additionally, toward the sustainability in the IUWS, identifying the more other effective factors (such as future temperature changes, carbon emission, catchment developments etc), the better system improvements can be achieved. This can help decision makers to adapt/improve the systems better to cope with the future changes.

With regard to the results described in this chapter, it is valuable to assess the potential *risk* that might be created due to exceedance of the water quality criteria in the recipient. This *risk* might affect decisions about the system upgrades (e.g. design) especially taking into account the future changes. Furthermore understanding the value of *risk*, under the future changes, may have the potential to increase the future costs but, on the other side, it can also enhance the system redundancy, i.e. ability to better deal with different future

conditions. Therefore, in Chapter 7, the potential of water quality to exceed the threshold value in the recipient and the associated impact are combined in a *risk* type measure which is then used as the IUWS (re)design optimisation objective.

CHAPTER 7

RISK-BASED IMPROVEMENT OF INTEGRATED URBAN WASTEWATER SYSTEM PERFORMANCE

7.1. 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 WFD (CEC, 2000), more attention is being given to developing risk-based approaches to water quality management (Sarang, *et al.*, 2008). For this purpose, the inherent uncertainties of the parameters of the future global changes need to be recognised and considered to estimate the risk. Also urban water quality decision-makers have to be aware of the risks (Willows & Connell, 2003) when planning for climate change and rapid urbanisation (IPCC, 2007). To address the aforementioned facts this chapter aims to develop a risk-based model to improve the IUWS performance in design and operational control under uncertain climate change and urbanisation scenarios. Additionally the aim here is to compare the impacts from the risk-based and the non-risk-based modelling approaches (developed in chapter 5 and 6) on water quality and the risk of water quality failures in recipient.

In section 7.2, the details of the risk-based approach developed to investigate water quality failures are presented. This is followed in section 7.3 by the application of the risk-based approach for improving the IUWS performance. In this section, the performance of the system is improved by applying the risk-

based approach in the operational control and design optimisation models developed in Chapter 5 and Chapter 6. The results will be discussed in section 7.4 and finally in section 7.5 a summary of findings will be presented.

7.2. Risk of Water Quality Failure in the Recipient

As already shown in chapters 5 and 6, DO concentration was used as an indicator of water quality necessary for the health of aquatic life in the recipient (see section 5.2.1 and section 6.2.2).

Ammonia is a ubiquitous contaminant of surface waters, entering watercourses from a variety of point and diffuse sources. It comprises two principal forms: the ionised ammonium ion (NH_4^+) and un-ionised ammonia (NH_3). The toxicity of ammonia to fish is attributable mainly to the un-ionised ammonia molecule. The proportion of un-ionised ammonia increases with increasing temperature and pH (e.g. at pH=7.5 most of it (i.e. 99 %) will be found as the Ammonium). Therefore un-ionised ammonia concentration was considered here as another indicator of water quality, important for the health of aquatic life in the recipient.

In the following it is important to describe and clarify the terms used to define the risk of water quality failure in the recipient in this study.

7.2.1. Risk of Water Quality Failure Definition

In this study water quality failure in recipient is defined as the water quality standard breach as follows:

- DO concentration below the Fundamental Intermittent water quality standard of 4 mg/l in the recipient;
- Un-ionised ammonia concentration above the Fundamental Intermittent water quality standard of 4 mg/l in the recipient.

IPCC (2007) in its 4th assessment report applied the standard definition of 'risk' defined by ISO/IEC Guide 73 (2002) as the 'combination of the probability of an event and its consequences' (see equation 7.1). This definition allows a variety of ways of combining probabilities and consequences. The following equation shows the general definition of aforementioned risk concept defined by ISO/IEC Guide 73 (2002). This equation later will be adapted according to the risk concept defined in this study.

$$\text{Risk} = \text{Consequence} \times \text{Probability} \quad (7.1)$$

UPM has expressed the Fundamental Intermittent Standards (FIS) in terms of concentration and duration thresholds for a range of return periods (RPs) for individual pollution episodes (Table 2.2 and Table 2.3 of the UPM). Further consideration of this research has led to the development of three sets of standards, relating to different levels of protection for episodes up to a return period of one year (FWR, 1998). The standards are based on the objective of no long-term detrimental effects on the aquatic ecosystem type and no fish mortality for wet weather pollution episodes of up to one year RP.

The aforementioned tables in the FIS imply that the risk of water quality failure is a function of water quality failure duration, Frequency/RP and violation as the following equation:

$$R_{WQF} = f(Dur_{WQF}, Freq_{WQF}(RP), V_{WQ}) \quad (7.2)$$

Where, R_{WQF} is the risk of water quality failure; Dur_{WQF} is the duration of water quality failure; $Freq_{WQF}$ is the frequency of water quality failure; RP is the return period of water quality failure and V_{WQ} is the water quality violation.

- The duration of water quality failure is defined as the length of period that the DO or un-ionised ammonia concentrations each fail to meet the threshold-based standard (see section 7.2.1).
- The frequency or RP of failure is an important factor for estimating the risk of water quality failure but it does not give a good evaluation of the risk value on its own. To address this issue, it should be noted that frequency/RP have interactions with other factors like duration of failure or total time period (of simulation) and can be affected by factors such as recovery period (the recovery period is the duration for exposure to un-ionised ammonia and DO during which fish, as the most sensitive species of aquatic lives introduced in the UPM, will be more susceptible to further exposure to any contaminants). Therefore all these points should be considered by the decision makers when applying frequency/RP for the risk calculations.

Additionally, according to UPM it is important to analyse the system performance over a suitable period of time so that the frequencies/RPs can be properly assessed. In line with this, UPM has presented an example in which the impacts of frequency/RP on water quality over the

period of one year have been assessed (for a hypothetical DO concentration record) but the shortage here is that no reliable sources found for this study investigated the impacts of frequency/RPs on water quality over shorter periods of time (e.g. less than a month).

In this study the IUWS performance is assessed over a 6 day rainfall period, so there is still some doubt whether frequency/RP impact on water quality should be considered for risk calculations or not. As this short rainfall period has been applied in the non-risk-based modeling approach (developed in Chapter 5 and Chapter 6), it was applied in this chapter too for the purpose of making later comparisons.

Frequency/RP impacts were not considered directly for risk although they are addressed to some extent as shown in equation (7.7) and the risk calculation steps illustrated in section 7.2.4. This issue indicates that the impacts of frequency/RP on water quality within short periods of time needs further work in future studies.

- Violation of the water quality standard is defined as the distance from the relevant threshold value, i.e. as follows:

$$V_{DO_t} = \max\{(4 - DO_t), 0\} \quad (7.3)$$

$$V_{AMMONIA_t} = \max\{(AMMONIA_t - 4), 0\} \quad (7.4)$$

where, DO_t is DO concentration at time t in mg/l and $AMMONIA_t$ is the un-ionised ammonia concentration at time t in mg/l.

7.2.2. Consequence of Water Quality Failure

The Environment Agency (EA) for England and Wales (2007) has published a number of reports about the proposed Environmental Quality Standards (EQSs) for substances falling under Annex VIII of the WFD. One of these reports concerns the proposed EQSs for un-ionised ammonia. In the EA's report (2007), the toxicity of un-ionised ammonia was investigated in nine freshwater species, with a focus on different fish species.

The results of these studies are summarised in Table 2.6 and Table 2.7 (of the EA's report) in the format of long term chronic data (between 10 days to 6 months) and short term acute data (between 1 to 5 days). In these tables, the effects of un-ionised ammonia toxicity on the aquatic lives are descriptively

explained. These descriptive impacts include mortality, emergence, hatching, growth survival and so on, but the largest effect is on mortality. The test results are expressed as impacts of concentration lethal to 50% of the organisms (LC50). Fishes were considered as the most sensitive species in the EA (2007) reports.

The table of long-term chronic data (Environment Agency, 2007) was considered in this study to evaluate the consequences of un-ionised ammonia failures in the IUWS. The cumulative CDF curve of un-ionised ammonia concentrations (see Figure 7.1) has been produced from the corresponding long-term chronic data, as shown in the EA (2007) report. The cumulative probability shown on the vertical axis of this figure represents the fraction of aquatic river life affected if the un-ionised ammonia concentration in the river is equal to or above the given value. As such, this probability is used here to represent the consequence of un-ionised ammonia failure. As it can be observed in Figure 7.1, this consequence is shown as a function of the logarithm of the un-ionised ammonia concentration.

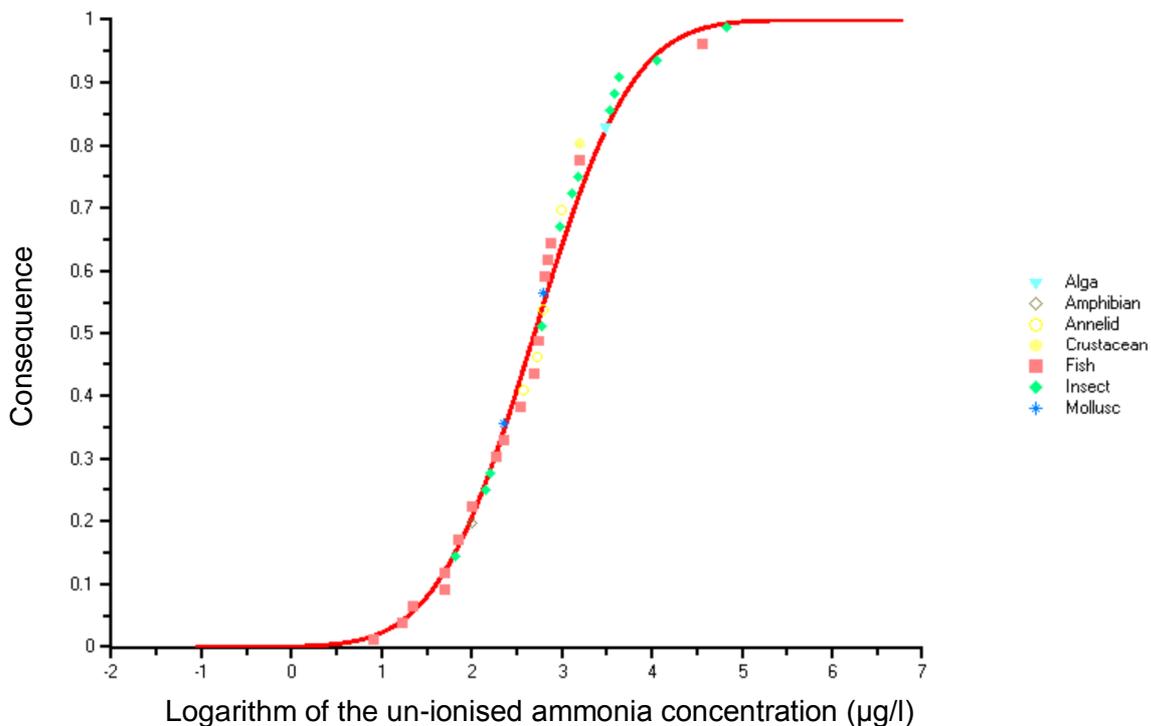


Figure 7.1 CDF of freshwater long term data for un-ionised ammonia concentration (µg/l) on fish mortality

The same methodology used by the EA to generate the curve shown in Figure 7.1, has been used here to generate the corresponding curve for the consequence of DO failure. Zweig *et al.* (1999) reported the DO concentration tolerances for different aquatic species in the river (see Table 7.1). These threshold values are used here to determine the consequence of the DO failure in the recipient by using the following procedure:

1. Sort the threshold DO concentration values shown in Table 7.1 in descending order;
2. Estimate the consequence of any DO concentration failure by using the Weibull formula. The Weibull formula is a standard method of estimating the probability of exceedance as follows:

$$P = \frac{m}{n+1} \quad (7.5)$$

where, p is the probability of exceedance for a given threshold DO concentration value, m is the given threshold DO value rank and n is the total number of threshold DO values. As in the case of un-ionised ammonia, the probability of exceedance represents the fraction of fish and other aquatic life in the river that is affected if the DO concentration is equal to or lower than the given threshold value and, as such, is used here to represent the consequence part of the risk of DO failure. The curve obtained using the above procedure is shown in Figure 7.2.

Table 7.1 Recommended DO concentration levels for aquaculture (Zweig, *et al.*, 1999)

Species	DO concentration (mg/l)	Comment
Tilapia, Carp, Eel	>5.0	Preferred
	3.0 - 4.0	Tolerable
Marine fish	> 6	Minimum
	> 6	Minimum
Salmonids	>5	Survive lower DO for a few hours
	>5.0	Recommended
	>1.5	Live for several days
	>1	Live for several hours
Warm water fish	<0.3	Lethal concentration
	Survive short exposure	
	Survive short exposure	
	Adults survive, eggs die	
Channel catfish	<0.5 (finger lings)	Survive short exposure
	0.5 (adults)	Survive short exposure
	2.0-3.0	Adults survive, eggs die
Shrimp	<5.0	Feed poorly, grow slowly
	0.7-1.4	Lethal concentration
Red swamp crawfish	<1	Survive short exposure
	<2	Adults crawl out

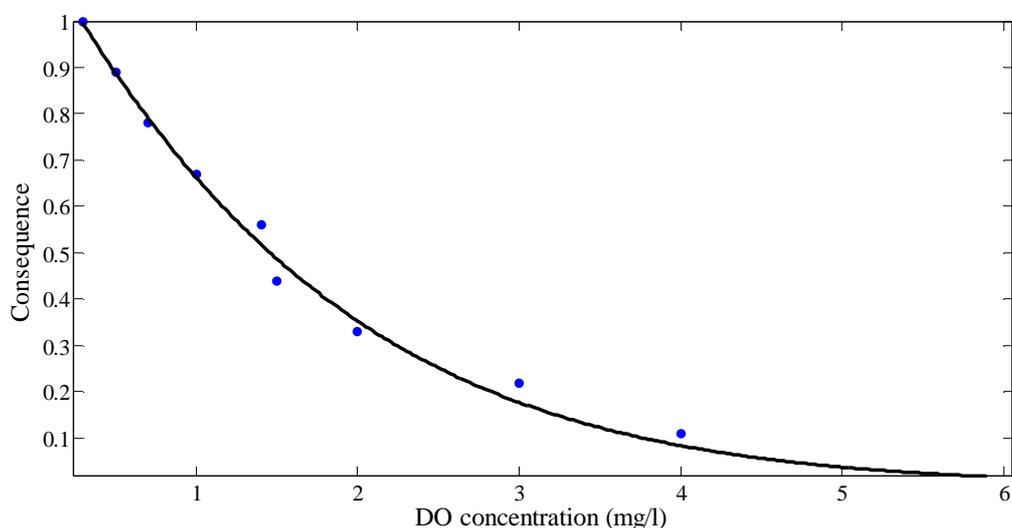


Figure 7.2 Empirical CDF of freshwater long term data for DO concentration (mg/l) on fish mortality

7.2.3. Probability of Water Quality Failure

Commonly, probability distributions are used to indicate the probability of an event occurrence. Because of the nature of the risk approach considered in this study, unlike the usual, probability distributions are not used for the purpose of

calculating the probability of water quality failures. Additionally as mentioned in section 7.2.2, “frequency/RP” of water quality failure is not used for this purpose and instead the “duration” of failure is used to calculate the probability of water quality failure as equation (7.6). Therefore in this study, the fraction of time that DO and un-ionised ammonia concentrations breach the 4 mg/l threshold is used to quantify the corresponding probabilities of failures, as shown in the following equation:

$$TF_{WQF} = \frac{t(DO < 4^{mg/l} \text{ or un-ionised ammonia} \geq 4^{mg/l})}{T} \quad (7.6)$$

where, TF_{WQF} is fraction of time with water quality failure; t is the time duration of a water quality failure in a DO/un-ionised ammonia concentration record; T is the total event simulation time.

Now for the purpose of risk formulation in this study, as an example the schematic hypothetical DO concentration record in a river was shown in Figure 7.3. In the aforementioned hypothetical figure it was assumed that DO concentration breaches 4 mg/l twice (so-called sags in UPM’s Figure 7.3).

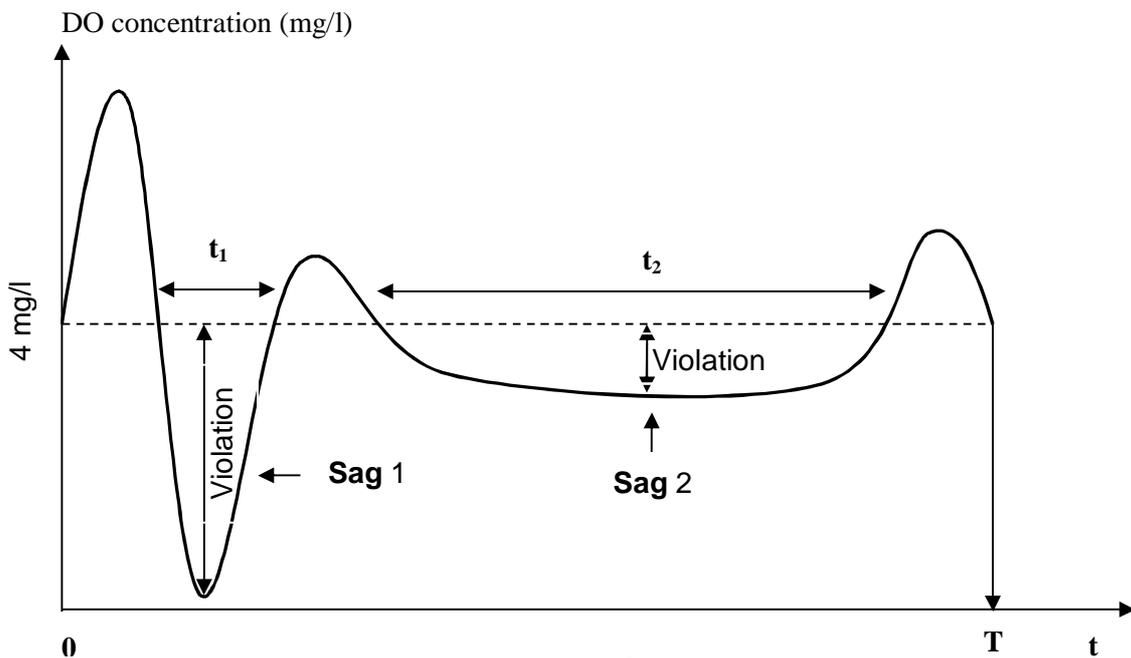


Figure 7.3 A hypothetical DO concentration record

In sag 1 (see Figure 7.3) the DO violation is significant but it happens in a short duration (i.e. t_1) and in sag 2 the DO violation is considerably less than sag 1 but it lasts for a longer duration (i.e. t_2). In sag 1, even though the violation is significant (therefore the consequence will be significant too) but as the duration of this failure is short so the time fraction of its failure (see equation 7.6) would

be small and eventually the final risk of failure value (multiplication of the big consequence in small time fraction failure) is likely (assumed) not to be larger than sag 2. Additionally in sag 2, even though the violation is not significant (therefore the consequence will not be significant too) it is possible that the risk of failure would be considerable due to its long breach time (i.e. because of significant time fraction of failure according to equation 7.6) which have the potential to harm the health of aquatic life considerably. In other words for accurate calculation of risk value, the interaction of “duration of water quality failure” and “water quality violation” should be considered as the following equation:

$$R_{WQF} = \sum_{i=1}^m \left(\frac{t_i}{T} \times Consequence_i \right) \quad (7.7)$$

where, R_{WQF} is the risk of water quality failure; i is the sag number; m is the total number of (failure frequencies) breaches; the other two terms (in the parentheses) are the time fraction of failure and the consequence defined in section 7.2.3 and section 7.2.4.

Eventually with regard to Figure 7.4, the steps to calculate the risk of water quality failure in this study can be summarised as the following:

1. Identify DO/un ionised ammonia breaches in DO/un-ionised ammonia concentration record (this can also consider the frequency of breaches to some extent pointed in section 7.2.2).
2. Calculate maximum violation in each sag for DO/ un-ionised ammonia with regard to equation (7.3)/ equation (7.4).
3. Calculate the consequence of maximum violation for DO/un-ionised ammonia from Figure 7.1/Figure 7.2.
4. Calculate the probability of water quality failure in each sag for DO/ionised ammonia according to equation (7.6).
5. Calculate the risk of water quality failure according to equation (7.7) in each sag for DO/un-ionised ammonia.
6. Sum risk values calculated in each sag aiming to find the total risk value.

7.2.4. Uncertainties in Risk Modelling

The climate change parameters used in this chapter are RD and RI, i.e. the same as in Chapter 5 and Chapter 6. The urbanisation parameters considered

are POP, IMP and PCW, together with the same value ranges used in Chapter 5 and Chapter 6 and presented in Table 4.1 (see section 4.4.1.2).

In this chapter only the uncertainties associated with the urbanisation parameters were considered directly. This was done because it was shown in Chapter 4 that the urbanisation parameters have major impacts on the quality of water in the river. The uncertainties associated with the climate change parameters were not considered directly here but rather indirectly, by quantifying their potential impacts via the modified DWF (i.e. water consumption).

In this chapter due to the uncertainties considered in the urbanisation parameters two new scenarios are defined to update SCB and SCC as: scenarios D (SCD) and scenario E (SCE). All the details of SCD and SCE are the same as SCB and SCC (see section 5.2.2) with only difference being that uncertainties (see section 7.3.1) are considered in the urbanisation parameters.

The uncertainty in all three urbanisation parameters was characterised using the uniform PDF. This was done because the urbanisation parameter values are not precisely known and there is not enough data available to estimate the actual empirical PDFs.

This uncertainty was quantified by using the LHS method with 20 samples (Fu, *et al.*, 2009). This quantification was also done using a larger number of samples (e.g. 50 samples) in limited number of tests and similar fitness values were obtained. The reason for this is that: (a) the use of Latin Hypercube technique enables good coverage of the uncertainty space with a small number of samples, due to the stratified nature of these samples, (b) small number of uncertain urbanisation parameters are considered in the study (three only) and (c) large computational times involved when optimising under uncertainty.

To propagate the aforementioned urbanisation parameters' uncertainties in the risk-based model calculation algorithm, a few updates are required to the first and second steps of the optimisation process flowchart shown in Figure 5.1. The aforementioned updates are shown in the in Figure 7.4:

1. Randomly generate the initial population for all the input parameters (see section 7.3.1) except for the urbanisation parameters.

2. Generate 20 samples for the urbanisation parameters POP, IMP and PCW using LHS method with a uniform distribution.
3. Obtain the fitness value of the chromosomes in the initial population (in step 1) by calculating the average fitness value of each chromosome in terms of the 20 samples generated (in step 2).
4. Apply the non-domination sorting algorithm to determine the rank and crowding distance for each chromosome.

As from step 4 in Figure 7.4 to the last step of the optimisation process is the same as the optimisation flowchart shown in Figure 5.1 therefore the rest of the flowchart is referenced to Figure 5.1.

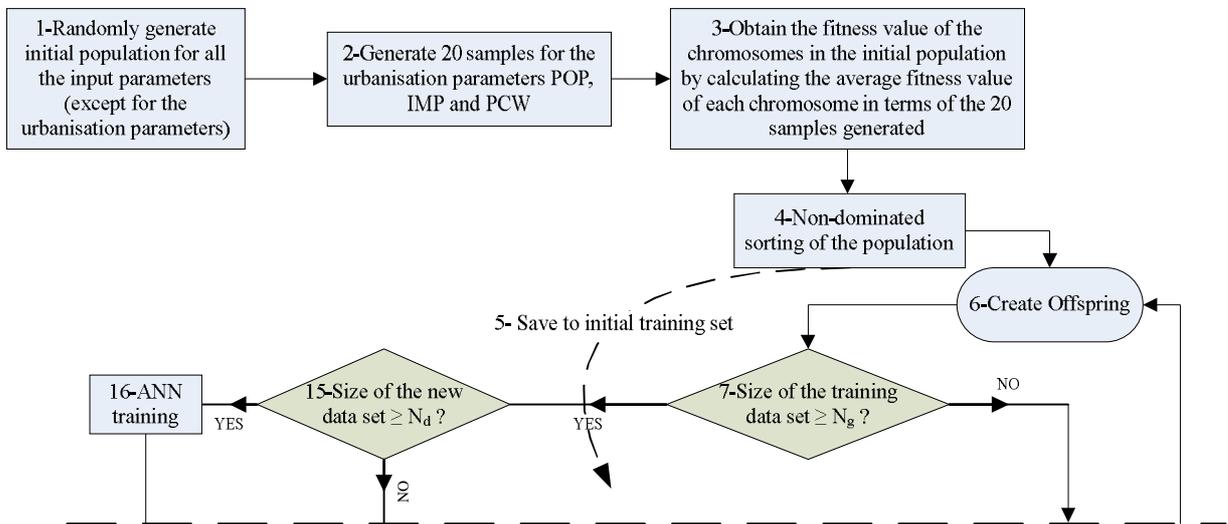


Figure 7.4 Updated optimisation flowchart for the risk-based modelling approach

7.3. Risk-based IUWS Optimisation

7.3.1 Optimisation Problems

Two risk-based optimisation problems are formulated and solved here, the IUWS operational control problem and the IUWS design problem. The rationale behind this, is to see how much the existing risks can be reduced by improving system operation only and also, by redesigning the system.

The risk-based IUWS operational control problem is formulated as a two-objective optimisation problem:

- Minimise the average risk (i.e. expected risk) of DO failure;

- Minimise the average risk (i.e. expected risk) of un-ionised ammonia failure.

Decision variables used here are as in the operational control optimisation model in Chapter 5 (see section 5.2.1), i.e. as follows:

- maximum sewer system outflow rate;
- maximum WWTP inflow rate and;
- threshold triggering emptying of the storm tank located at the inlet to the WWTP.

The associated boundary values shown in Table 4.1 are used to constrain the optimisation process.

The risk-based IUWS design problem is formulated using the same two risk-based objectives mentioned above. Decision variables used in this model are the same variables defined and used in the design optimisation model shown in Chapter 6 (see section 6.2.2), i.e. as follows:

- maximum outflow rates of storage tanks ST_2 , ST_4 and ST_6 ;
- contribution-coefficients of storage tanks ST_2 , ST_4 , ST_6 and ST_7 and;
- three aforementioned operational control optimisation variables.

The associated boundary values shown in Table 6.1 (and Table 4.1) are used to constrain the IUWS design optimisation process.

The iterative procedure presented in Figure 6.2 to determine the minimum storage capacity increase (i.e. c) in the design optimisation model in chapter 6 needs a minor change in steps 3 for the risk-based design model developed in this chapter. The goal of the risk-based design model in this chapter is to iteratively reduce the total IUWS redesign cost until the optimal Pareto-fronts can meet a low risk level. *This low risk level was assumed equal or less than 1% in this chapter.* Figure 7.5 shows the minor change carried out in the aforementioned flowchart.

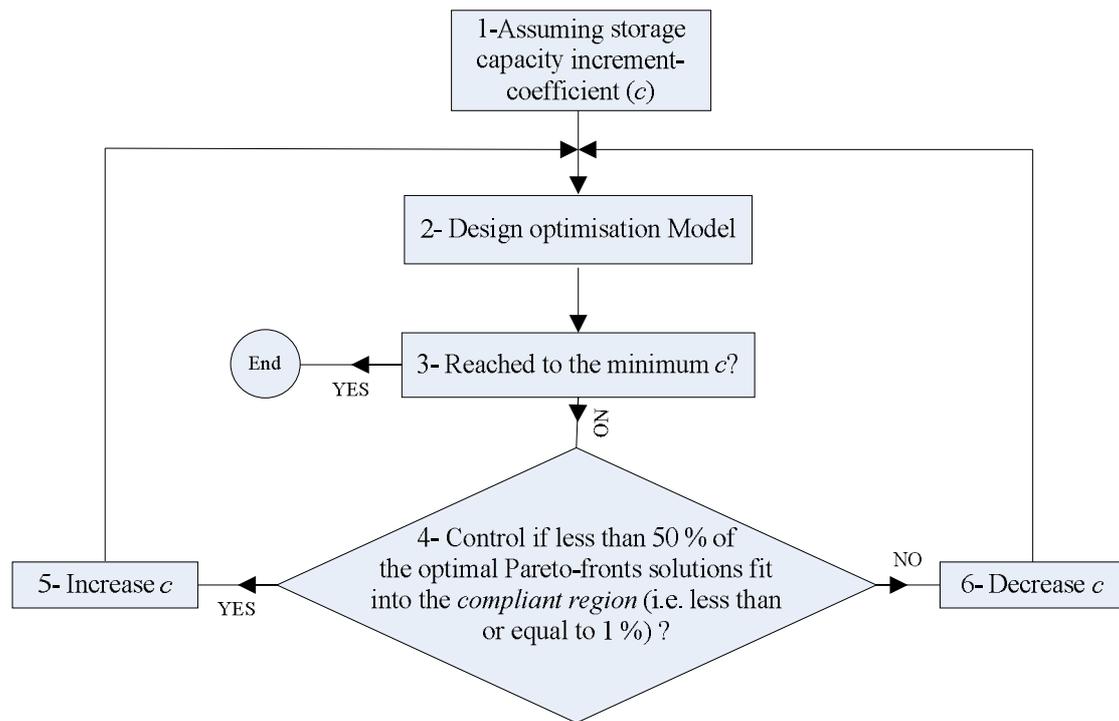


Figure 7.5 Schematic diagram of the iterative procedure to determine the minimum c in the risk-based design model

Assuming 1% as a criterion for determining the minimum redesign cost in this study can lead to the new challenge of determining the tolerable risk level to maintain the health of aquatic life. Determining such a criterion is subjective and difficult to estimate and indeed needs further researches discussed in the future work section.

The redesign cost in this chapter is calculated using equation (6.3).

The risk-based optimisation problems are solved using the MOGA-ANN β optimisation algorithm described in section 5.3.

7.4. Optimisation Results and Discussion

7.4.1. Description

The case study described in Chapter 4 and used in all previous chapters, is used here as well. The risk-based methodology shown in this chapter is demonstrated here on the case study by solving the two optimisation problems. The two climate change scenarios defined in Chapter 5 (i.e. SCB and SCC), are also used in this chapter to investigate the impacts of the risk-based modelling approach on river water quality. The aim is to illustrate the operational control and design potential in the IUWS under the risk-based modelling approach and

reveal the extent of its effectiveness in mitigating the negative impact of climate change (RD, RI) and urbanisation parameters' uncertainties (IMP, POP, PCW) on river water quality.

7.4.2. Risk-Based Operational Control Optimisation

Initially the risk-based modelling approach was applied to SCA, SCB, SCC, SCD (i.e. BC_{SCD}) and SCE (i.e. BC_{SCE}) to estimate the risk of water quality failures under climate change and urbanisation in the river and before system improvement. The risk values estimated above under these scenarios are presented in Table 7.2, Figure 7.6 and Figure 7.7.

Table 7.2 Risk of DO and AMM/un-ionised ammonia failure in the river

	Without urbanisation parameters' uncertainties			With urbanisation parameters' uncertainties		
	BC_{SCA} / BC	BC_{SCB}	BC_{SCC}		BC_{SCD}	BC_{SCE}
Risk of DO failure (%)	0	3.92	0	Average risk of DO failure (%)	5.85	5.2
Risk of AMM/un-ionised ammonia failure (%)	0	0.87	0	Average risk of AMM/un-ionised ammonia failure (%)	14.26	6.47

In both Figure 7.6 and Figure 7.7 the risk values (see Table 7.2) are represented with different symbols. The “filled star” shows the risk values (i.e. risk of DO and AMM/un-ionised ammonia failure) under SCA (i.e. BC_{SCA}/BC). In Figure 7.6 the “triangle” shows the risk values under SCB (i.e. BC_{SCB}) and the “filled triangle” shows the risk values under SCD (i.e. BC_{SCD}). Also the points D_1 , E_1 shown in Figure 7.6 and Figure 7.7 will be introduced later in this section and the points D_2 and E_2 will be presented in Figure 7.17 and Figure 7.18 in subsection 7.4.3. The compliant region for risk values (i.e. 1% risk criterion introduced in section 7.3.1) was shown with dashed lines in Figure 7.6 and Figure 7.7.

As it can be observed in Figure 7.6 and Figure 7.7 (also Table 7.2), the risk of water quality failure in the river under SCA (i.e. the BC_{SCA}/BC point) is zero. In other words, according to the risk-based modelling approach, the current setting of the IUWS in both operational control and design is good enough to cope with the base rainfall in SCA (see section 3.3.2 and section 5.2.2). This indicates that by applying the risk-based modelling approach to SCA, there is no need to

improve the system operational control or design (see BC_{SCA}/BC point in Figure 7.6/Figure 7.7) but according to the non-risk-based modelling approach (see section 5.2.1), the water quality indicators cannot fully meet the compliant region and the system needs further improvement (see BC_{SCA}/BC point in Figure 5.6). This demonstrates that the system modelling approach can have an impact on possible system adaptation.

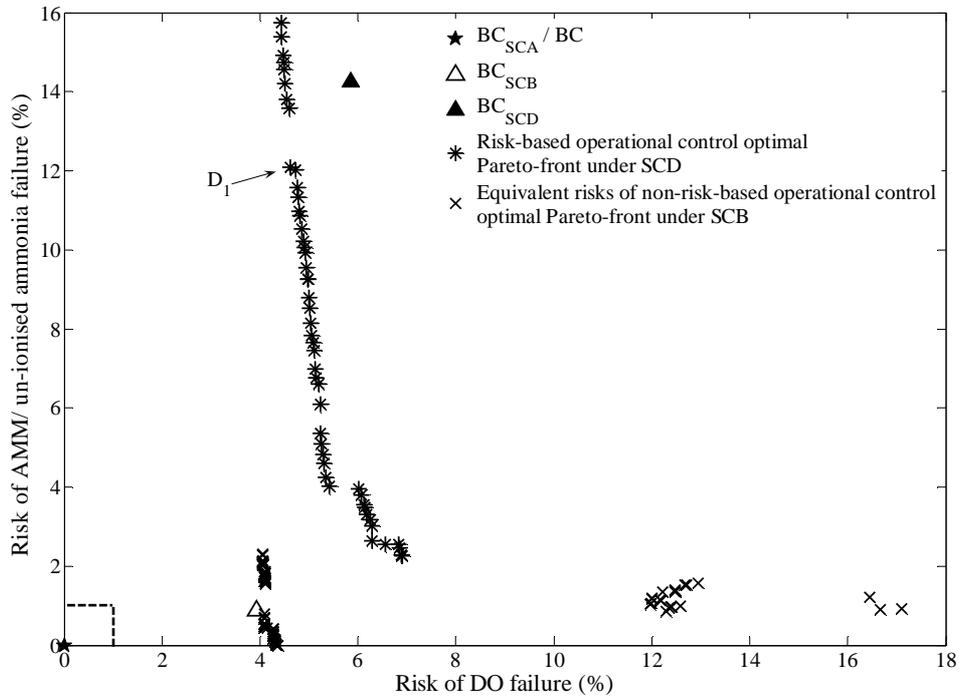


Figure 7.6 Risk of water quality failure before and after operational control optimization under SCA, SCB and SCD (i.e. under RD)

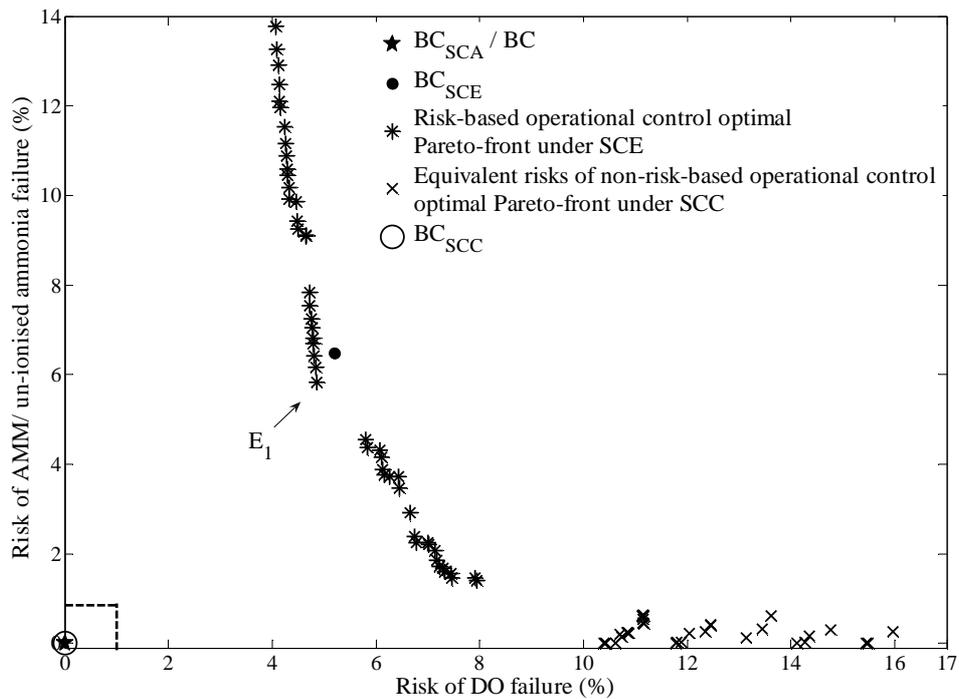


Figure 7.7 Risk of water quality failure before and after operational control optimisation under SCA, SCC and SCE (i.e. under RI)

As it can be observed in Figure 7.6 and Table 7.2, a risk of water quality failure in the river exists under SCB (i.e. BC_{SCB} point shown with triangle), particularly the risk of DO failure which is significant and cannot meet the compliant region. These risks arise from water quality breaches in the river (because of CSOs' volume increase as a consequence of rainfall depth increase), as shown in the BC_{SCB} point in Figure 5.6. The reason for the higher risk of DO failure than the AMM failure is due to the increased AMM load which, in turn, leads to increased DO depletion and reduced AMM concentration, due to dilution. Therefore according to the risk-based modelling approach, the system needs further improvement to meet this criterion. This is in line with the conclusions obtained from the non-risk-based modelling approach in Chapter 5 representing the necessity of system improvement to meet the compliant region under SCB (i.e. for DO and AMM concentrations).

The risk-based modelling approach was applied to SCD and the risk values obtained are presented in Table 7.2 and Figure 7.6 (the BC_{SCD} point shown with filled triangle). As can be seen in Table 7.2 and Figure 7.6, both the risk of DO and AMM/un-ionised ammonia failures significantly increased in the river in the BC_{SCD} point comparing to the BC_{SCB} point. These increases arise from uncertainties considered in the urbanisation parameters in SCD which have the potential to consider several possible states of the urbanisation parameters varying between their minimum and maximum value ranges and this can increase the risk. The same conclusion as SCB was obtained for SCD in consequence of the risk-based modelling approach applied to improve the system performance. In other words, with regard to the risk values obtained under SCD (see BC_{SCD} point in Table 7.2 and Figure 7.6), the compliant region is not met here and therefore the system needs further improvement to cope with the risk of water quality failure in the river under the future climate change and urbanisation parameter's uncertainties under SCD in this study.

Figure 7.7 and Table 7.2 show that the risks of DO and AMM/un-ionised ammonia failures under SCC (i.e. BC_{SCC}) are zero. In other words according to the risk-based modelling approach, the current setting of the IUWS in terms of both operational control and design, is good enough to cope with the climate change parameter RI in SCC. Comparison of the BC_{SCC} point in Figure 7.7 (i.e. under the risk-based modelling approach defined in this chapter) with that in Figure 5.6 (i.e. under the non-risk-based modelling approach in Chapter 5) shows that although the risk of DO and AMM under BC_{SCC} is zero (see Table 7.2) but DO and AMM concentration in Figure 5.6 cannot meet the compliant region (i.e. 4 mg/l water quality criterion in Chapter 5, see BC_{SCC} in Figure 5.6). The reason for this can be observed in the record of DO and AMM concentration shown later in Figure 7.7 to Figure 7.11. In other words, the current setting of the system (i.e. operational control parameters and design) can cope with the future climate change parameter RI under the risk-based modelling approach while the non-risk-based modelling approach shows the necessity of system improvement under SCC (see Figure 5.6). As a result, the decision about a proper system modeling approach under SCC is also important for similar reasons discussed earlier.

The risk-based modelling approach was applied to SCE (i.e. BC_{SCE} point) and the risk values obtained are presented in the Table 7.2. As can be observed in Figure 7.7 and Table 7.2, the risk values in the river increased considerably in the BC_{SCE} point comparing to the BC_{SCC} point. These increases arise from the uncertainties considered in the urbanisation parameters in SCE with the same reason mentioned above for SCD. As a result with regard to the risk values obtained under SCE (see BC_{SCE} point in Table 7.2 and Figure 7.7), the system needs further improvement in SCE to cope with the risks generated under the future climate change parameter RI and the urbanisation parameter's uncertainties considered in this study.

In order to further illustrate the impact of the risk-based and non-risk-based modelling approaches on water quality parameters in the river, the DO and AMM/un-ionised ammonia concentrations during the 6 days rainfall (i.e. base rainfall, RD and RI) in the aforementioned scenarios (i.e. BC_{SCA}/BC , BC_{SCB} , BC_{SCC} , BC_{SCD} and BC_{SCE} points in Figure 7.6 and Figure 7.7) are presented in Figure 7.7, Figure 7.9, Figure 7.10 and Figure 7.11. In all these figures the horizontal dashed line shows the 4 mg/l water quality criteria for both DO and AMM/un-ionised ammonia concentrations in the critical reaches river reach 10 (i.e. the reach with maximum AMM/un-ionised ammonia concentration) and river reach 40 (i.e. the reach with minimum DO concentration) in the river.

In the above figures, the “solid” lines shows the DO and AMM/un-ionised ammonia concentrations in the BC_{SCA}/BC point, the “dashed” lines shows the DO and AMM/un-ionised ammonia concentrations in the BC_{SCB} and BC_{SCC} points and the “marked solid” lines shows the DO and AMM/un-ionised ammonia concentrations in BC_{SCD} and BC_{SCE} points.

Generally, as shown in Figure 7.8 and Figure 7.9 (same in Figure 7.10 and Figure 7.11), the DO and AMM/un-ionised ammonia concentrations both can meet the 4 mg/l water quality criterion under SCA (i.e. in BC_{SCA}/BC point shown with solid line).

Figure 7.8 shows that the DO concentration is depleted (i.e. breaches 4 mg/l) under SCB (in BC_{SCB} point with dashed line) because of the rainfall depth (i.e. RD) increase in this scenario which consequently increases CSOs as well. This DO depletion is intensified under SCD when the urbanisation parameters' uncertainties are considered in this scenario (in BC_{SCD} point with marked-solid line). The same observations exist in Figure 7.9 about AMM/un-ionised ammonia concentration under SCB and SCD. The climate change parameter RD (only in SCB) and then urbanisation parameters' uncertainties (in SCD) bring about AMM/un-ionised ammonia concentrations failure in the river (see BC_{SCB} and BC_{SCD} points).

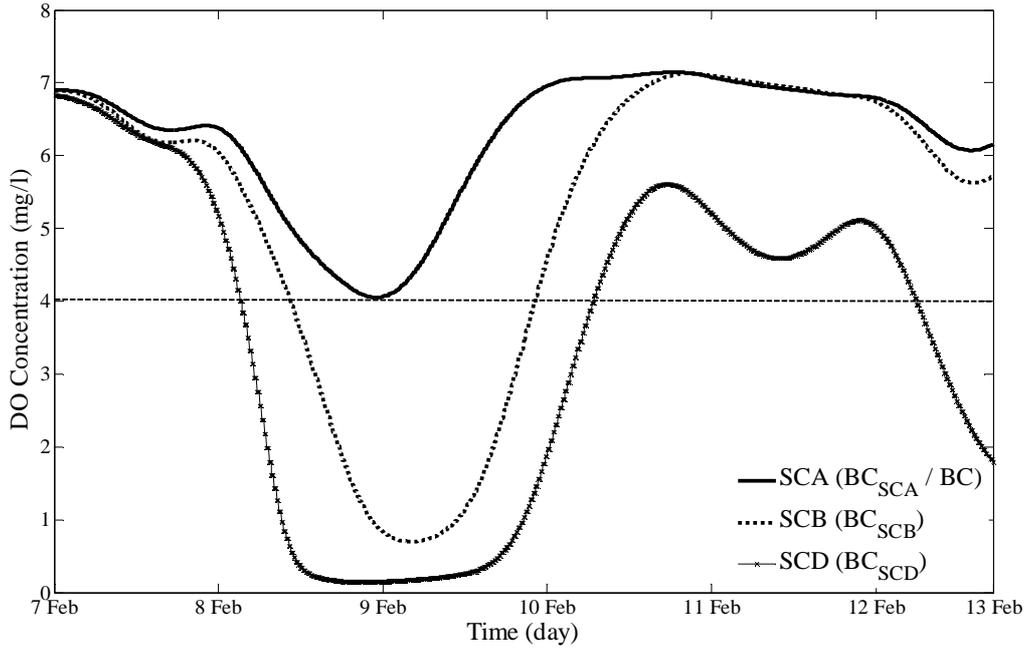


Figure 7.8 DO concentration in the river under SCA, SCB and SCD

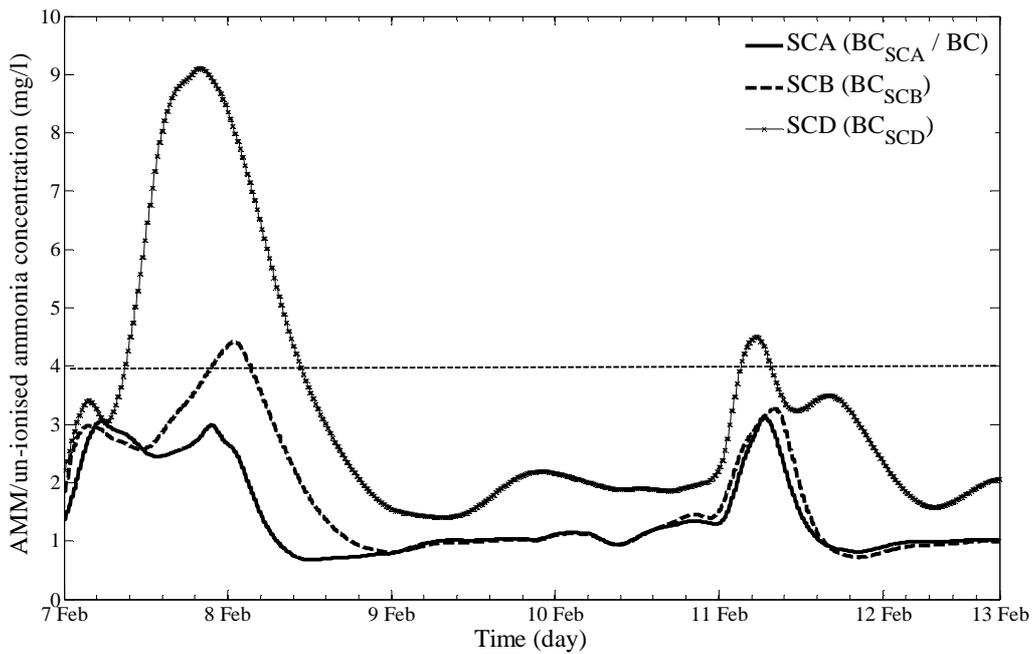


Figure 7.9 AMM/un-ionised ammonia concentration in the river under SCA, SCB and SCD

Figure 7.10 and Figure 7.11 show the DO and AMM/un-ionised ammonia concentrations for the BC_{SCA}/BC, BC_{SCC} and BC_{SCE} points. As it can be observed from Figure 7.10 and Figure 7.11, both DO and AMM/un-ionised ammonia concentrations can almost meet the 4 mg/l water quality criterion under SCC (i.e. in BC_{SCC} point). This is in line with the zero risk values shown in Figure 7.7 and Table 7.2. In other words under the climate change parameter RI, there is no concern about the risk of water quality failure according to the risk-based modelling approach in this study while there is concern about that under the non-risk-based modelling approach (see BC_{SCC} point in Figure 5.6 which fails to fully meet the compliant region). This near zero risk can be justified with the short duration of DO breach and its small violation (which may cause no significant failure consequence) shown in Figure 7.10 and also no breach for AMM concentration under SCC shown in Figure 7.11. Figure 7.10 also shows that the DO concentration is depleted under SCE. This depletion is not only because of rainfall intensity change (i.e. RI) but because of the urbanisation parameters' uncertainties considered under SCE which intensifies the DO concentration deterioration. The same result is observed in Figure 7.11 about AMM/un-ionised ammonia concentration under SCE. The urbanisation parameters' uncertainties worsen the AMM/un-ionised ammonia concentrations in the river in this scenario. The reasons were explained above.

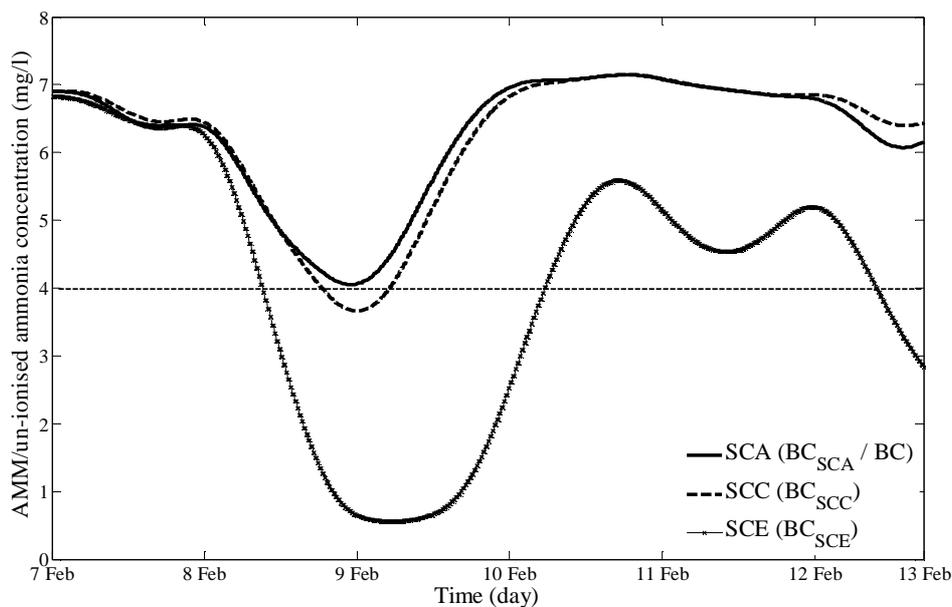


Figure 7.10 DO concentrations under SCA, SCC and SCE

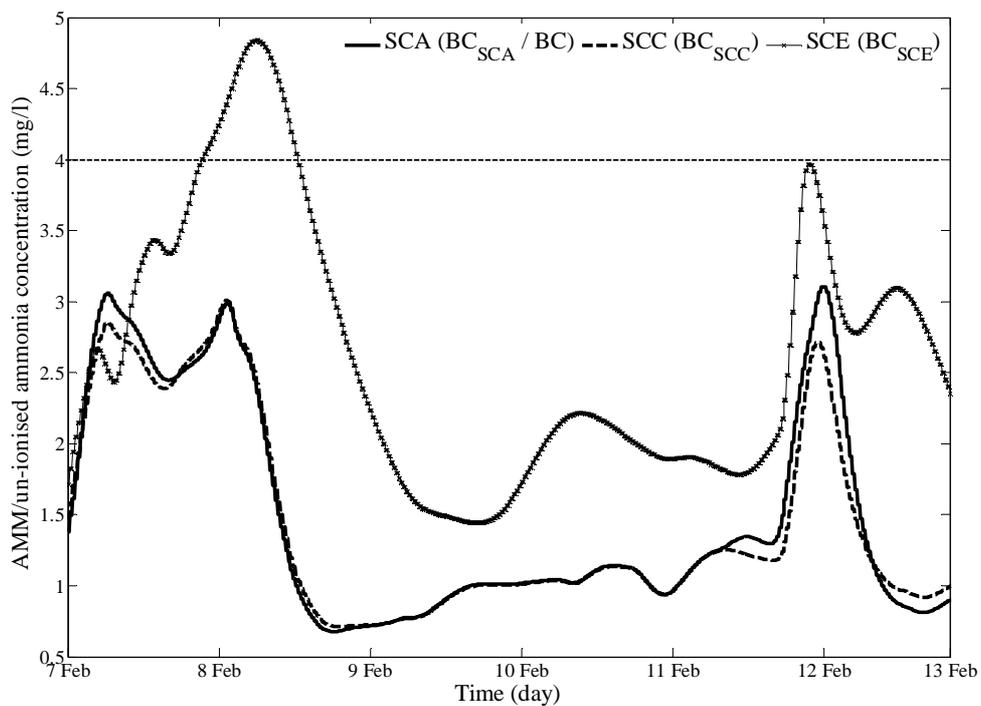


Figure 7.11 AMM/un-ionised ammonia concentrations under SCA, SCC and SCE

CSOs are one of the main reasons for water quality deteriorations in the river that need to be controlled (see Chapter 5). Figure 7.12 shows the expected (i.e. average) total CSO volume (averaged over 20 samples) in the system under each scenario (i.e. in BC_{SCA}/BC , BC_{SCB} , BC_{SCC} , BC_{SCD} and BC_{SCE} solutions). As mentioned before the points D_1 , E_1 , D_2 and E_2 will be introduced later in this chapter. The comparison of the CSO volumes under each scenario can represent scenarios having more potential to deteriorate the quality of water under the future climate changes and urbanisation.

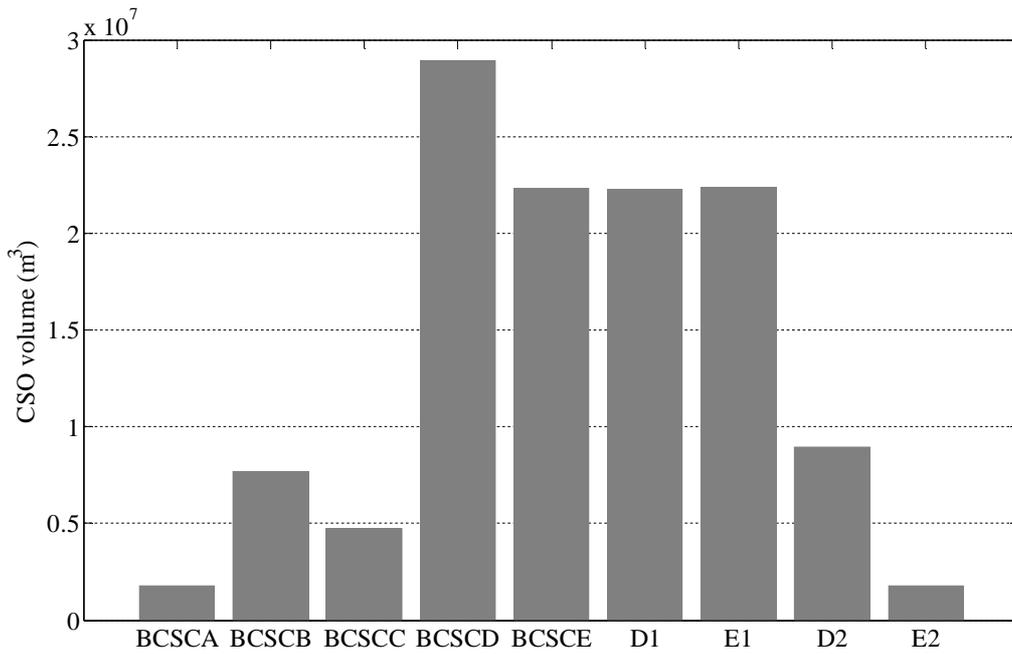


Figure 7.12 CSO volume (m³)

As Figure 7.12 shows, CSO volume under SCA (i.e. in the BC_{SCA}/BC point) is lower than the other scenarios. In other words this volume of CSO is tolerable (because of no change in climate and urbanisation parameters assumed) in the river according to the risk-based modelling approach but according to the non-risk-based modelling approach is not tolerable as the BC_{SCA}/BC point failed to meet the compliant region (see Figure 5.6).

Additionally, CSO volume under SCB (i.e. BC_{SCB}) is larger than under SCC (i.e. BC_{SCC}) as a consequence of the rainfall depth increase under this scenario. According to the risk-based modelling approach the risk value under SCB is not tolerable (see risk values in BC_{SCB} in Table 7.2 which are more than compliant region) and this is in line with the non-risk-based modelling approach cannot meet the compliant region (see BC_{SCB} point in Figure 5.6).

A different observation exists for SCC in Figure 7.12. The system can 'bear' the risk (i.e. zero risk in Table 7.2) even with CSO increases under SCC (comparing to SCA) but the non-risk-based modelling approach showed that the aforementioned CSOs are not tolerable as the rainfall intensity changes under SCC and this causes both DO and AMM concentrations fail to meet the compliant region in Figure 5.6.

Also CSO volume under SCD (i.e. BC_{SCD}) and SCE (i.e. BC_{SCE}) increased significantly comparing to SCB (i.e. BC_{SCB}) and SCC (i.e. BC_{SCC}). This arises from the urbanisation parameters' uncertainties considered under SCD and SCE. Additionally CSO volume under SCD is more considerable than SCE because of more rainfall volume. This is in line with the larger risk values under SCD than SCE (see Table 7.2).

As shown in Figure 7.6 and Figure 7.7, before completing any system improvement under SCD and SCE (i.e. in BC_{SCD} and BC_{SCE} points), the system fails to reach the compliant region here. These fails indicate that the system under both SCD and SCE cannot tolerate the risk and needs further improvement. Initially the risk-based operational control model was applied to SCD and SCE to improve the system performance and mitigate the risk of water quality failure in the river by optimising the operational control of the system.

The optimal Pareto-front obtained from the risk-based operational control optimisation under SCD and SCE were presented with the “star” symbol in Figure 7.6 and Figure 7.7 respectively. Although improvements (i.e. risk reduction) are observed under the operational control optimisation (with comparing the BC_{SCD} and BC_{SCE} points to the operational control optimal Pareto-fronts of SCD and SCE), still the operational control optimal Pareto-fronts are far from the compliant region.

Additionally as it can be observed from the operational control optimal Pareto-front in Figure 7.6 and Figure 7.7, the risk of failure for AMM/un-ionised ammonia is greater than the risk of failure for DO. This indicates that according to this modelling approach, combining the future climate changes with the urbanisation parameters' uncertainties have the potential to increase the risk of AMM/un-ionised ammonia failure over DO failure (because of direct impact of the urbanisation parameters on DWF quality and quantity).

In order to further illustrate the impact of the risk-based operational control optimisation on river water quality, a comparison is carried out between the DO and AMM/un-ionised ammonia concentration before and after system improvement (i.e. after operational control optimisation). For this purpose, a nominated solution (i.e. to the BC_{SCD} and BC_{SCE}) from the optimal Pareto-front of SCD and SCE in Figure 7.6 and Figure 7.7 was selected (i.e. D_1 and E_1). Then DO and AMM/un-ionised ammonia concentration failures in D_1 and E_1 during the rainfall are presented in Figure 7.13 and Figure 7.14 (for SCD), Figure 7.15 and Figure 7.16 (for SCE). In the figures the DO and AMM/un-ionised ammonia concentrations in BC_{SCD} and BC_{SCE} points are presented with a “solid” line and in D_1 and E_1 with the “dashed” lines. The points D_2 and E_2 will be introduced later in section 7.4.3.

With the risk-based operational control optimisation, the DO concentration was improved from the BC_{SCD} point (i.e. solid line) to D_1 (i.e. dashed line) but still fails to meet the 4 mg/l (Figure 7.13). The improvement arises from the CSO volume decrease shown in Figure 7.12 in both D_1 and E_1 (i.e. cross and star symbols in Figure 7.12). The same observations exist about max-AMM/un-ionised ammonia concentration in Figure 7.14. The risk-based operational control optimisation is still not enough to meet the 4 mg/l standard.

The comparison of the BC_{SCD} (solid line) with D_1 (dashed line) in Figure 7.13, shows that the AMM/un-ionised ammonia concentration was improved more than DO concentration with the risk-based operational control optimisation. This can indicate the increased effectiveness of the risk-based operational control optimisation to reduce the AMM/un-ionised ammonia failure than DO failure in the selected points in this study.

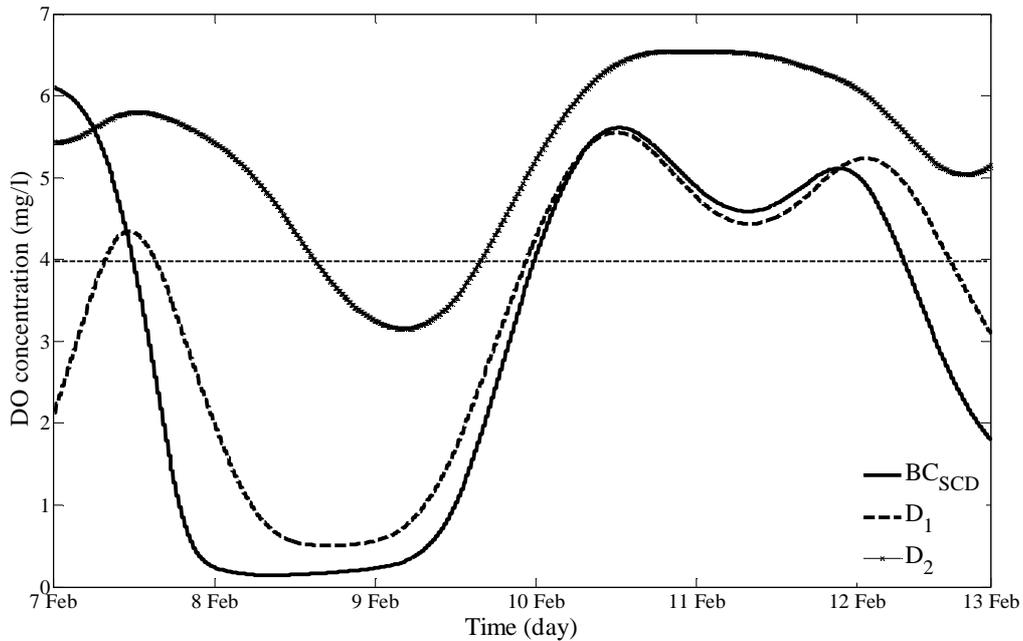


Figure 7.13 DO concentration under SCD before and after system improvement

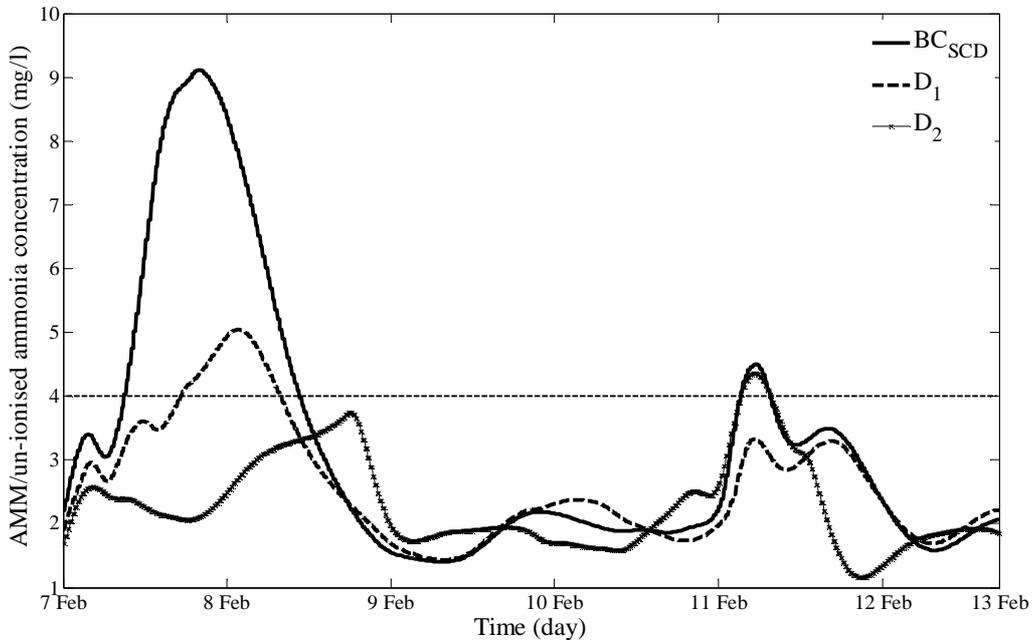


Figure 7.14 AMM/ un-ionised ammonia concentration under SCD before and after system improvement

The same results are obtained in Figure 7.15 and Figure 7.16 under SCE. These results imply that although the risk-based modelling approach improves the min-DO and max-AMM/un-ionised ammonia concentration comparing to BC_{SCD} and BC_{SCE} , it still is not enough to fully meet the 4 mg/l standard in E_1 and D_1 . The min-DO and max-AMM/un-ionised ammonia concentration improvement in E_1 is not great enough (comparing to the BC_{SCE}). This is probably due to the negligible CSO volume decrease under E_1 (comparing to the BC_{SCE}) shown in Figure 7.12 (shown with cross and star symbols). As a result, the risk-based operational control optimisation has potential to improve water quality to some extent under future climate change and urbanisation parameters' uncertainties but still is not good enough to meet the compliant region in this study.

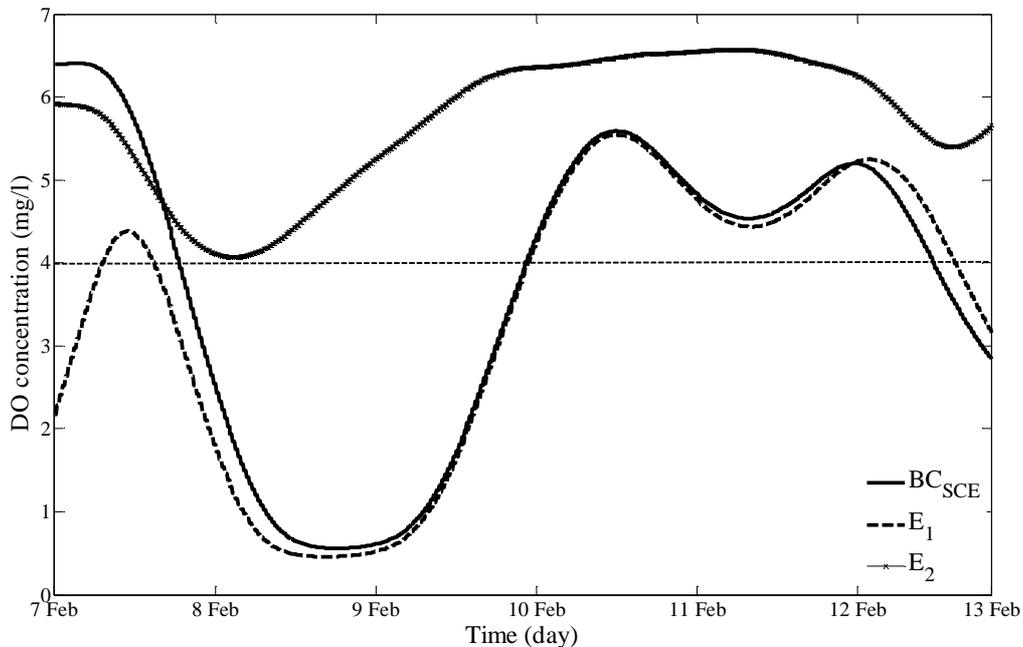


Figure 7.15 DO concentration under SCE before and after system improvement

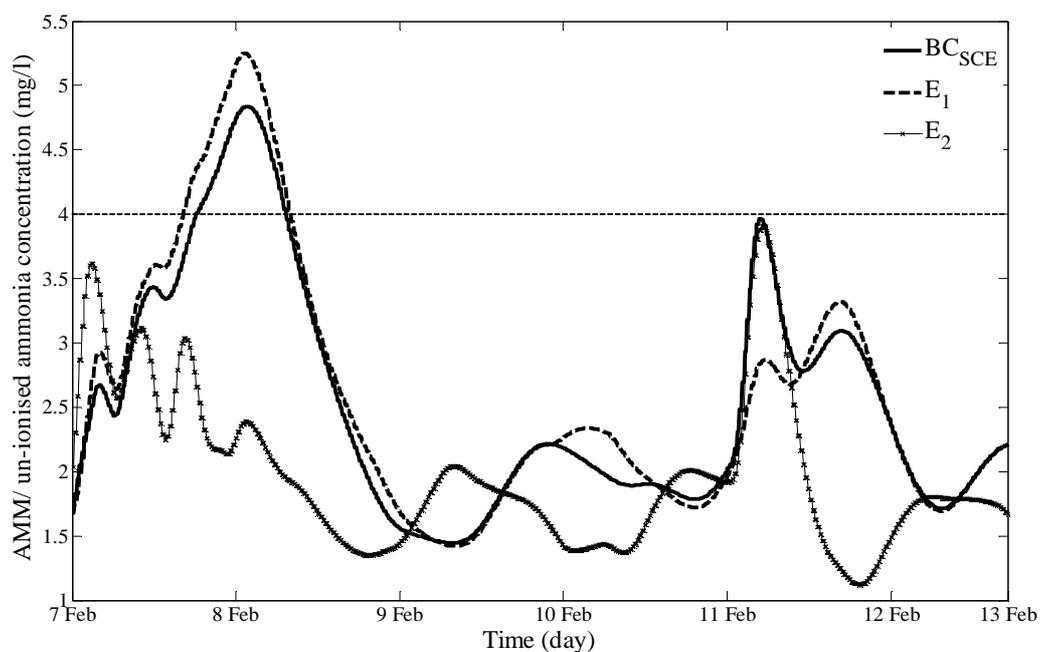


Figure 7.16 AMM/ un-ionised ammonia concentration under SCE before and after system improvement

For the purpose of further comparison between the risk-based operational control optimisation and the non-risk-based operational control optimisation modelling approaches and their impacts on the systems' performances (i.e. water quality indicators), the equivalent risk values of the operational control optimal Pareto-front of SCB and SCC (see Figure 5.6) were estimated and shown in Figure 7.6 and Figure 7.7 (with "crosses"). This aims to investigate whether the non-risk-based modelling approach can meet the compliant region with regard to the importance of the risk-based modelling approaches for the future sustainable systems required.

Therefore as shown in Figure 7.6 and Figure 7.7, the equivalent risk values of AMM concentration in the non-risk-based operational control optimal Pareto-front (see Figure 5.6) can meet the compliant region but the equivalent risk of DO fails to see the compliant region .

This indicates that the non-risk-based operational control modelling approach in this study is able to control the risk of AMM/un-ionised ammonia failure to some extent (even for the solution which cannot meet the compliant region in Figure 5.6) but fails to meet the very low DO risk (even for the solutions within the compliant region in Figure 5.6). There are different observations about the risk of water quality failures under the risk-based modelling approach in this study. As observed in Figure 7.17 and Figure 7.18, there are more concerns about the risk of AMM/un-ionised ammonia failure than DO failure in this study.

7.4.3. Risk-Based Design Optimisation

As indicated in the previous section, similar to the non-risk-based modelling approach, the risk-based operational control modelling approach is not good enough to reduce the risk of water quality failure in this study. Therefore the risk-based design optimisation model is applied to SCD and SCE. As mentioned in section 6.2.1, this approach aims to find the design potentials required to reduce the risk of water quality failure in the river.

The optimal Pareto-fronts obtained are presented with “circle” symbol shown in Figure 7.17 and Figure 7.18. As it can be observed in Figure 7.17, the minimum storage capacity increase required under SCD to meet the low risk level (i.e. 1 %) is about 200% (see section 7.3.1 for more detail). In other words with adding twice of the current storage capacity of the IUWS to the catchment, the system will be able to meet less than 1 % risk criterion for DO and AMM/un-ionised ammonia under SCD. Similar improvement can be observed in Figure 7.18 for SCE. The minimum storage capacity increase required so the risk-based design model optimal Pareto-front can meet the compliant region, was estimated at about 150% in this study.

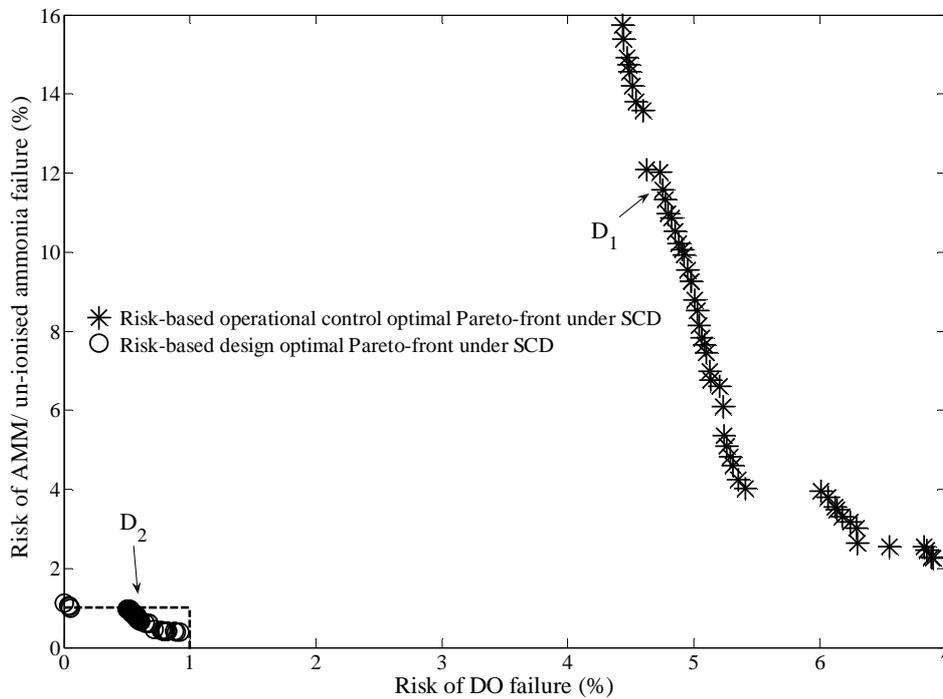


Figure 7.17 Risk-based operational control and design model optimal Pareto-front under SCD (i.e. under RD)

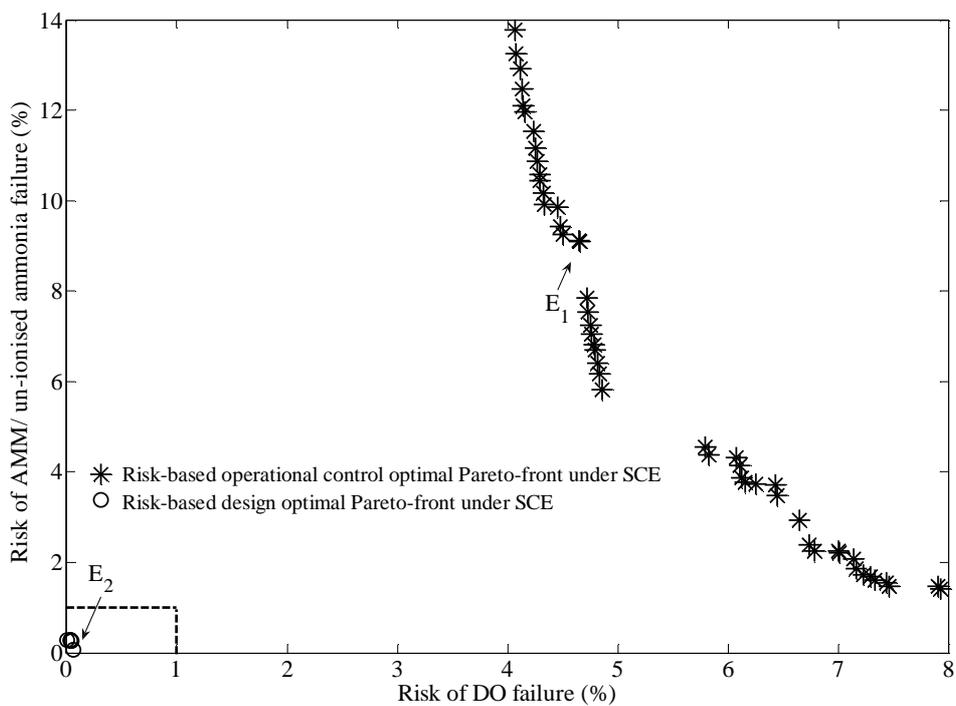


Figure 7.18 Risk-based operational control and design optimisation under SCE (i.e. under RI)

In order to further illustrate the impact of the risk-based design optimisation on the risk reduction under SCD and SCE, two solutions were selected from the optimal Pareto-front shown in Figure 7.17 and Figure 7.18 (i.e. D_2 and E_2). The DO and AMM/un-ionised ammonia concentrations in D_2 and E_2 were presented in Figure 7.13, Figure 7.14, Figure 7.15 and Figure 7.16 (marked line). As shown, almost in all the aforementioned figures, DO and AMM/un-ionised ammonia can meet the 4 mg/l water quality standard. This is in line with the risk reduction (i.e. less than 1%) carried out under the risk-based design optimisation model and shown in Figure 7.17 and Figure 7.18.

Similar to the operational control optimisation model, there is a question here as to whether the non-risk-based design model optimal Pareto-front can meet the compliant region here. To answer this question, the equivalent risk values of the non-risk-based design model optimal Pareto-front of SCB in Figure 6.3 were calculated and shown in Figure 7.19 (see X-is). Also the risk-based design model optimal Pareto-front of SCD is shown (again here in addition to Figure 7.6) in Figure 7.19 too (see stars).

Figure 7.19 indicates the equivalent risk values are very far from the low risk values assumed in this study (less than 1%) and also the risk-based design optimisation model Pareto-front. This indicates that the 100% minimum storage capacity increase required for SCB in Chapter 6 under the non-risk-based modeling approach, is not enough here to meet the compliant region. As a result the modelling approach and the uncertainties of the involved parameters have important role in estimating the minimum storage capacity increase and consequently the adaptation costs required in this study.

Finally it should be noted that one of the main reasons of the significant risk reduction and water quality improvement under the risk-based design optimisation modelling approach is the significant CSO reduction under this approach which shown in Figure 7.12 for D_2 and E_2 in this study.

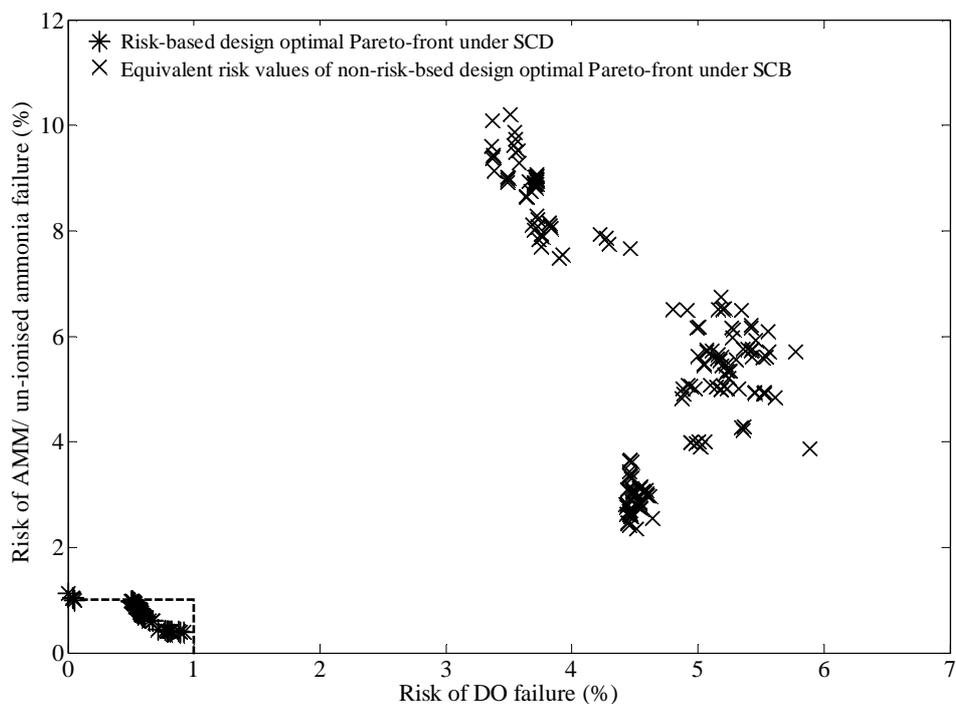


Figure 7.19 Comparison of the risk-based design optimal Pareto- front under SCD and equivalent risk values of the non-risk-based design optimal Pareto-front under SCB (i.e. under RD)

7.5. Summary

In this chapter, an attempt was made to reduce the negative impact of climate change and urbanisation parameters' uncertainties on the risk of water quality failure in the river by optimising (i.e. improving) the operational control and design of the IUWS. Additionally the extent of the effectiveness of the risk-based modelling approach in maintaining the water quality in the river was compared with the non-risk-based modelling approach (developed in Chapter 5 and 6).

The results obtained from the risk-based modelling approach in this chapter illustrate that the risk-based operational control optimisation has potential to reduce the risk of water quality failure to some extent under future climate change and urbanisation parameters' uncertainties but still is not good enough to meet the compliant region (e.g. 1 % risk criterion defined in this chapter). Similar to the non-risk-based modelling approach, a design model under the risk-based modelling approach is required to improve the system performance to meet the compliant region. The results obtained showed that the improvements' efforts in the risk-based design model under SCD are more than under SCE in this study as the combination of the increased volume of rainfall with the urbanisation parameters' uncertainties has more negative impact on the risk of water quality failure in the river.

In addition to this, the risk-based modeling approach results obtained showed that combining the future climate change with the urbanisation parameters' uncertainties has potential to increase the risk of AMM/un-ionised ammonia failure more than DO failure (because of direct impact of the urbanisation parameters on DWF quality and quantity) while this was more critical about DO concentration under the non-risk-based modeling approach in Chapter 5 and Chapter 6.

The design improvement under the risk-based modelling approach needs more storage capacity than the non-risk-based design improvement.

Under the risk-based modelling approach in this study the system can meet both risk criterion assumed and also water quality standards (i.e. 4 mg/l) while under the non-risk-based modelling approach, the strategies which met the water quality standards, could not meet the risk criterion defined. This indicates

considering the risk-based modelling approach to maintain the water quality under the future changes, have the benefit of meeting both water quality standards and the acceptable risk level together in this study.

Generally this chapter showed that the system modelling approach is vital in any likely system adaptations required. Meanwhile selecting the water quality criteria/ standards has significant impact on the aforementioned adaptations. Therefore selecting a proper modelling approach is subjective and depends on the decision makers' preferences and the problem in hand.

A summary of the conclusions obtained made in this thesis is presented in the next chapter.

CHAPTER 8

CONCLUSIONS

8.1. Introduction

An integrated modelling approach was applied to the urban wastewater system to improve its performance under potential future climate change and urbanisation. In line with this task, several contributions are presented to address the following objectives. The objectives as originally formulated were to:

1. Investigate the impact of climate change and urbanisation on the IUWS performance in terms of the receiving water quality. In line with this, different indicators of climate change and urbanisation are selected for evaluation.
2. Improve the performance of the IUWS (under future climate change and urbanisation) by improving the operational control of the IUWS aiming to maintain the quality of water in the river. This is initiated by applying a scenario-based approach to describe the possible features of future climate change and /or urbanisation.
3. Improve the performance of the IUWS (under the future climate change and urbanisation) by improving the design of the IUWS under the scenarios identified above (i.e. the scenarios where the operational control optimisation cannot meet the water quality standards in the recipient).

4. Improve the performance of the IUWS under future climate change and urbanisation by reducing the risk of water quality failures to maintain the health of aquatic life. This is initiated by considering the uncertainties involved with the urbanisation parameters considered. The risk concept is applied to estimate the risk of water quality breaches for the aquatic life.

8.2. Contribution of the Thesis

The contributions are elaborated in the following:

1. A novel application of a LSA (Tornado graph) and GSA (RSA) method to the IUWS under the future changes aiming to determine the most significant climate change, urbanisation and operational control parameters in terms of the receiving water quality in a single case study used. The integrated modelling approach applied with the LSA and GSA methods used can consider the interactions between the parameters to give a better evaluation of the results. A water quality criterion of 4 mg/l criteria is used here to evaluate the IUWS performance in terms of water quality indicators.
2. Applying a scenario-based approach to describe the possible features of the future climate change and urbanisation with their considered input parameters. These scenarios are divided into two groups; climate change scenarios and combined climate change with urbanisation scenarios. The effective parameters determined from the LSA and GSA, are used to make the aforementioned scenarios. These scenarios are used in the entire thesis for evaluation.
3. A development of a novel operational control optimisation model (including climate change parameter, urbanisation parameters and operational control parameters) to improve the IUWS performance to maintain the quality of water under the future climate change with/without urbanisation. The results achieved from this novel model can show what future scenarios would need more attention, as well as how much operational control efforts would be required in the future to meet the quality of water criteria defined. Additionally the results obtained can

show whether the operational control optimisation is good enough to improve the quality of water under future changes.

4. A development of a novel design model to improve the IUWS performance in terms of improving the quality of water under the future climate change with/without urbanisation. The results achieved from this novel model can show what future scenarios need more attention under future changes, as well as how much design efforts would be required in the future to meet the quality of water criteria defined. Additionally the results obtained can show whether the design optimisation is good enough to improve the quality of water under future changes.
5. The novel application of the sewer system storage tanks' capacities in the design optimisation model to improve the IUWS performance under the future climate changes with/without urbanisation. The sewer system storage tanks have the potential to control the CSOs as the main reasons of deteriorating the quality of water in the IUWS.
6. A development of a novel quantitative approach to estimate the risk of water quality failures in the water recipients under the future climate change and urbanisation uncertainties. In this novel approach, the risk concept is the product of the probability of water quality failure multiplied to the consequence of water quality failure. Also the 1% was assumed as the acceptable risk level in the IUWS in this study.
7. Development of a novel risk-based model to improve the IUWS performance in terms of operational control under the future climate change and urbanisation uncertainties. In this novel model the expected risk of water quality failures were considered as the objective of the risk-based optimisation model. The operational control parameters used in the non-risk-based optimisation model, are used as the decision variables here. The results obtained from the risk-based operational control optimisation can show whether this model is good enough to reduce the risk of water quality failure in the future to see the acceptable risk level.

8. Development of a risk-based model to improve the IUWS performance in design under the future climate change and urbanisation uncertainties. In this model the optimisation objectives are the same as the risk-based operational control model. In addition to the operational control parameters, design parameters (i.e. sewer system storage tank capacities) are used as the decision variables here. The results obtained from the risk-based design optimisation model can show the storage capacity increases required under future changes.
9. The novel development of the improved MOGA-ANN optimisation method (i.e. MOGA-ANN β). This novel model can better generalize the original MOGA-ANN method by bringing the crowding distance, in addition to the rank, to the algorithm of the MOGA-ANN to select the good solutions for the analysis. Also the Bayesian method used in this novel algorithm to improve the accuracy of training predictions.
10. The novel application of the MOGA-ANN β as a substitution of the simulation model used in the optimisation process aiming to reduce the computational time in the entire thesis while preserving the accuracy. This algorithm could save considerable time in the risk-based and non-risk-based optimisation modelling process.

8.3. Conclusions

In the fulfillment of the aforementioned objectives, a number of significant outcomes have been achieved in this study based on a single case study used and are presented in the following:

1. Identifying the significant climate change, urbanisation and operational control system parameters is very important. Selecting the suitable sensitivity analysis method(s) is important for identifying these parameters as it enables speeding up the follow on analyses.
2. The LSA and GSA (e.g. RSA applied in this study) methods are useful to identify the most significant input parameters. The GSA methods can indicate the most effective parameters more precisely than LSA methods

as they consider the interaction among all the considered indicators (parameters) of the system. These methods can be very efficient when there are several parameters which need to be considered and their interactions can have significantly influence on the evaluation results.

3. In a scenario-based approach applied in this thesis, it is important to provide scenarios which can be real representatives of the future changes. In other words they have to be able to specify the boundaries of the likely decision space (i.e. upper and lower values of input parameters).
4. It can be concluded from the operational control optimisation of the IUWS that: (a) Operational control optimisation of the IUWS under only climate change scenarios can meet the water quality standard up to some extent. The quality of water is more deteriorated when climate change increases the wastewater flow; (b) Operational control optimisation of the IUWS under the combined climate change with urbanisation scenarios is not good enough to cope with the future changes. This arises from the increased volume of DWF and runoffs which have more potential to deteriorate the quality of water; (c) Additionally with regard to the less effective operational control optimisation in isolation in the future to deal with the water quality criteria, other techniques need to be applied to improve the performance of the IUWS.
5. Climate changes, which bring about more wastewater volume into the system, have more potential than ones with less wastewater volume to deteriorate the quality of water in recipients. These deteriorations are intensified when the urbanisation impacts are added to climate change. Therefore to adapt the IUWS under the future climate change, it is important to control the increased volume of wastewater (e.g. CSOs) that originates from these changes. Also urbanisation parameters are important as they are the main sources of input pollutants' loads into the wastewater (e.g. in DWF or in the surface runoffs). Therefore it is important to obtain a real estimation of the pollutants' loads in the wastewaters.

6. CSOs are the main sources of water quality deterioration in the recipient. For that reason storage tanks in the sewer systems have an important role in controlling the CSOs and maintaining the quality of water. Therefore the capacity of the storage tanks is a key factor in the IUWS design model under the future climate change and urbanisation. Consequently with any changes in the design of the IUWS (e.g. storage tanks' capacities), the operational control of that (outflow rates of the storage tanks) need to be adjusted to use the increased capacity efficiently. In other words the design and operational control of the IUWS are dependent and need to be combined to operate more efficient. Also in addition to the storage capacity increase, the optimal distribution of the increased storage capacity is important to reduce the CSOs and to maintain the quality of water. Therefore in the design model, the contribution of each storage tanks (from total the increased storage capacity) to be included in the sewer system is required. This helps preserving the quality of water with no unnecessary costs for the operational control or redesigning in the future.
7. Optimisation of the IUWS performance, especially with the tools like Simulink/Matlab needs a high computational power and is time demanding. Therefore selecting optimisation algorithms which can meet the optimisation requirements in terms of the compatibility, efficiency, time and so on is important. The MOGA-ANN β algorithm was an efficient algorithm in this study which could save a lot of time and computational power (up to nearly about 70% in this study).
8. Selecting the input parameters of the risk-based model is very important as their associated uncertainties bring about different risk levels to the model.
9. The risk-based modelling approach has the benefit of meeting both compliant regions considered in this study (i.e. 4 mg/l for the non-risk-based modelling approach and 1% assumed in this study for the risk-based modelling approach) while under the non-risk-based modelling

approach, the risk-based modelling approach compliant region (i.e. 1% assumed) cannot be met in this study.

10. An integrated modelling approach is vital in any likely system adaptations required under the risk-based and the non-risk-based modelling approaches to improve the quality of water. In line with this, selecting the “water quality criteria/ standards/ tolerable level of risk” has significant impacts on the aforementioned adaptations.

8.4. Present Work Limitations

In the fulfillment of the research carried out in this PhD thesis, it is beneficial to point out to the limitations existed in this study as the following:

1. With regard to the integrated modelling approach applied for this study, there was the lack of an original integrated real case study comprised of a sewer system, a WWTP and a river with enough data from all the subsections considered. In line with this a hypothetical (i.e. semi-real) case study was considered for this study with a number of simplifications (such as the hydrological approach applied to model the sewer system rather than a detailed pipe network) performed for modelling different components of the system. This lack of information/data can be extended to the required data for the purpose of calibration and validations of the system as well. These were important limitations as first a real-life case study would behave different than a hypothetical case study and consequently the conclusions obtained would be different and second enough calibration data have influence on the reliability of results obtained.
2. SIMBA5 tool used for the IUWS modelling, is an efficient tool in many aspects but the most important limitations/drawbacks with this tool is the commercial hard key (Dongle) that it needs to be triggered for the simulation process. This limits the user to just one computer (that is connected to that) and with regard to the expensive price of this tool sometimes it is impossible to buy more than one dongle. This research study really suffered from this limitation.

3. The consequences of DO depletion for different types of aquatic life in the river were an important need in this study for the purpose of estimating the risk values. There was a lack of quantitative research in this field (even by the ecologists) but similar studies have been carried out for a group of pollutants by EA (2007) to estimate their consequences on the aquaculture. Further works on this was included in the future work recommendations.
4. Also this study suffered from lack of information about the tolerable risk levels by the aquatic life to evaluate the risk-based modelling approach performance developed in this study. The real tolerable risk levels have potential to change essentially the future adaptation techniques recommended here. In this study a tolerable risk level was assumed to proceed the study but this issue needs detailed investigations which included in the future recommendations.

8.5. Future Work Recommendations

1. It is recommended to apply the methodologies/modelling approaches developed here on a real-life case study which will have the real data in all elements of IUWS and not only in WWTP. These approaches would significantly benefit from a real-life case study.
2. It is recommended to apply Regional Climate Models (RCM) to quantify the impact of climate change on the IUWS performance in terms of DWF quality and quantity, sewer system storage capacities, sewer system runoffs, sewer system operational control parameters, WWTP quality and quantity (i.e. storm tank capacities, pumping stations, aeration rate) and finally recipient water quality and quantity. For instance the UKCIP09 (UK Climate Projections) provides climate information designed to help those needing to plan how they will adapt to a changing climate. The data is focused on the UK. This model has the possibility of considering the uncertainty existing in the climate change parameters. Therefore linking these GCMs with the IUWS simulation model can be a potential research in the future.

3. It is recommended to recognise and to consider other climate change, urbanisation and system parameters to analyse the IUWS performance under the future changes. Many factors can impact on the IUWS performance, and therefore consideration of more parameters, in addition to those introduced here, provide opportunities to achieve to more realistic results and evaluations. Examples of other climate change parameters (depending on the particular case study) could be temperature and sea level change; for urbanisation, examples include housing density, housing occupancy, land use change, water recycling and reuse systems etc; for the system parameters, they could include aeration rates in the aeration tanks in the WWTP, treatment capacity, membrane parameters etc.
4. Also it is recommended to expand the current study for additional substances such as COD, organic matters, nitrate, phosphorus etc. Each of these pollutants has their own impacts on water recipients' quality. Selection of each of which and/or a group of these depends on the case study in hand and the aim of the study.
5. It is recommended to consider the addition of more objectives (if required with the other optimisation technique than NSGA-II) to the IUWS optimisation model. These objectives could include the reduction of carbon emissions, cost and energy consumption etc. Considering more objectives has the potential to show that trade-off exists between different objectives in the real world. For example the pumping stations use energy to work but at the same time they emit carbon. Meanwhile the operational costs increase relative to the energy used and design costs relative to the system adaptations applied. Therefore it is difficult to obtain more realistic and optimal strategies and requires further investigations.
6. The expensive computational time required when combining these climate models with the IUWS and then applying an optimisation algorithm to them, can be a good start to apply meta-models e.g. MOGA-

ANN to reduce the computational time. There it is of interest to apply and if required to update the current “MOGA-ANN β ” algorithm or develop another algorithm in different cases. These updates can be comprised of different training/retraining data set size, different gridding size, other ANN parameters to improve the accuracy and speeding up the process, optimisation techniques other than NSGA-II (e.g. AMALGAM, spreadsheet-based etc).

7. Following the former future recommendation, it needs to be mentioned that in addition to the surrogate modelling approaches (like MOGA-ANN β in this study), new other modelling approaches exist. These recent approaches, for instance, include parallel computing and cloud computing methods which speed up the running aiming to reduce the computational time while the accuracy is preserved. It should be noted here that selecting a proper approach/method for this purpose depends on the end user of the model and the problem in hand.
8. It is recommended, in addition to increasing the storage tanks capacities in the design model, to consider other adaptation techniques to meet the water quality criteria e.g. Wastewater Treatment Works (WWTW). These WWTW, which are site specific, effective and may cost less. For example for the case study applied, which is located in an agriculture area, the possibility of some WWTW could be investigated to help the agriculture in this area with less financial resources. Other WWTW could consider an anaerobic WWTP which, in addition to treating the wastewater, can supply part of the energy required for the system operation.
9. The design cost was considered in this study and the operational control costs were not considered as they were similar in all the options. The operational control costs can be significant in the large case studies. Also, energy consumption and carbon emissions are other challenges in the operational control of the IUWS that need to be taken into account. These factors can be considered as the IUWS optimisation model objectives.

10. It is recommended, to enhance the application of the risk-based modelling approach in water quality management under future changes. This is initiated with estimating the minimum/maximum concentration of each water quality indicator required (for different levels of health) for different species of aquatic life. This task might require working with other disciplines such as ecologists. Also, in line with the aforementioned enhancement, it is required to estimate the consequence of different water quality indicators on different species of aquatic life (as CDF) in rivers (similar to un-ionised ammonia concentration carried out by Environment Agency). It should be noted that generating such CDFs is difficult as the frequency and duration of water quality failures have an impact on the values of the consequence. This was a challenge in this study for DO failure. Therefore a detailed study is required to investigate the impact of duration and frequency of water quality failure on the consequence. Additionally determining such minimum/maximum concentration for each water quality indicator can assist to generate an accurate CDF of the probability of water quality failures. It is obvious such accurate estimations can give a more accurate risk value.
11. Determining the level of tolerable risks of water quality failures for different species of aquatic life is very important. These tolerable risk criteria have significant impacts on the evaluation of model results, the level of adaptation techniques required, and the likely costs of adaptation techniques etc. This tolerable risk level was assumed to be 1% for DO and un-ionised ammonia in this study but the fact is that more investigations and collaborations between water engineers and ecologists would be required for this purpose.

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