Decision Making Methods for Water Resources Management Under Deep Uncertainty

Submitted by Thomas Peter Roach to the University of Exeter

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I certify that all material in this thesis which is not my own work has been identified and that no material has previously been submitted and approved for the award of a degree by this or any other University.

Signature: ……………………………………………………………..

Abstract

Substantial anthropogenic change of the Earth's climate is modifying patterns of rainfall, river flow, glacial melt and groundwater recharge rates across the planet, undermining many of the stationarity assumptions upon which water resources infrastructure has been historically managed. This hydrological uncertainty is creating a potentially vast range of possible futures that could threaten the dependability of vital regional water supplies. This, combined with increased urbanisation and rapidly growing regional populations, is putting pressures on finite water resources. One of the greatest international challenges facing decision makers in the water industry is the increasing influences of these "deep" climate change and population growth uncertainties affecting the long-term balance of supply and demand and necessitating the need for adaptive action. Water companies and utilities worldwide are now under pressure to modernise their management frameworks and approaches to decision making in order to identify more sustainable and cost-effective water management adaptations that are reliable in the face of uncertainty.

The aim of this thesis is to compare and contrast a range of existing Decision Making Methods (DMMs) for possible application to Water Resources Management (WRM) problems, critically analyse on real-life case studies their suitability for handling uncertainties relating to climate change and population growth and then use the knowledge generated this way to develop a new, resilience-based WRM planning methodology. This involves a critical evaluation of the advantages and disadvantages of a range of methods and metrics developed to improve on current engineering practice, to ultimately compile a list of suitable recommendations for a future framework for WRM adaptation planning under deep uncertainty.

This thesis contributes to the growing vital research and literature in this area in several distinct ways. Firstly, it qualitatively reviews a range of DMMs for potential application to WRM adaptation problems using a set of developed criteria. Secondly, it quantitatively assesses two promising and contrasting DMMs on two suitable real-world case studies to compare highlighted aspects derived from the qualitative review and evaluate the adaptation outputs on a

practical engineering level. Thirdly, it develops and reviews a range of new potential performance metrics that could be used to quantitatively define system resilience to help answer the water industries question of how best to build in more resilience in future water resource adaptation planning. This leads to the creation and testing of a novel resilience driven methodology for optimal water resource planning, combining optimal aspects derived from the quantitative case study work with the optimal metric derived from the resilience metric investigation. Ultimately, based on the results obtained, a list of suitable recommendations is compiled on how to improve the existing methodologies for future WRM planning under deep uncertainty. These recommendations include the incorporation of more complex simulation models into the planning process, utilisation of multi-objective optimisation algorithms, improved uncertainty characterisation and assessments, an explicit robustness examination and the incorporation of additional performance metrics to increase the clarity of the strategy assessment process.

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ATP – Adaptation Tipping Points
BW – Bristol Water
BWRZ – Bristol Water Resource Zone
CART – Classification and Regression Tree
CCRA – Climate Change Risk Assessment
CO_2 – Carbon Dioxide
CP – Current Practice
DAPP – Dynamic Adaptive Policy Pathways
Defra – Department for Environment, Food and Rural Affairs
DMM - Decision Making Method
DO – Deployable Output
DS – Decision-Scaling
DWI – Drinking Water Inspectorate (UK Gov)
DYAA – Dry Year Annual Average
EA – Environment Agency (UK Gov)
EBSD – Economics of Balancing Supply and Demand
EPA – Environment Protection Agency (US Gov)
FAO – Food and Agriculture Organization (of the United Nations)
FF – Future Flow
GCM – Global Circulation Model
GW – Groundwater
GWP – Global Water Partnership
HMSO – Her Majesty's Stationary Office (UK Gov)
IG – Info-Gap decision theory
IPCC – Intergovernmental Panel on Climate Change
IWRM – Integrated Water Resources Management
LAP – Laplace Principle of Insufficient Reason
LP – Linear Programming
MBR – Membrane Bioreactor
MCDA – Multi-Criteria Decision Analysis
MDO – Minimum Deployable Output
MFFD – Multi-Functional Flood Defences
MOEA – Multi-Objective Evolutionary Algorithms
MORDM – Many-Objective Robust Decision Making
MOVA – Many-Objective Visual Analytics
MR – Minimax Regret
MRF – Minimum Residual Flow
NERA – National Economic Research Associates
NPV – Net Present Value
NSGA-II – Non-dominated Sorting Genetic Algorithm II
Ofwat – Office of Water Services (UK Gov)
ONS – Office for National Statistics

PDF – Probability Density Function
PRIM – Patient Rule Induction Method
PV – Present Value
RAND – Research AND Development (US corporation)
RCM – Region Climate Model
RCP – Representative Concentration Pathway
RDM – Robust Decision Making
RO – Robust Optimisation
ROA – Real Options Analysis
SNWRZ – Sussex North Water Resource Zone
SRES – Special Report on Emissions Scenarios
SW – Southern Water
UK – United Kingdom
US – United States (of America)
UKCIP – UK Climate Impacts Programme
UKCP09 – UK Climate Projections 2009
UKCP18 – UK Climate Projections 2018
UKWIR – UK Water Industry Research
UM – Universal Metering
VIDEO – Visually Interactive Decision-making and Design using Evolutionary multi-objective Optimisation
WEF – World Economic Forum
WMT – Wald's Maximin Theory
WRM – Water Resources Management
WRMP – Water Resources Management Plan
WRPG – Water Resources Planning Guideline
WTW – Water Treatment Works
WWTW – Wastewater Treatment Works

Chapter 1. Introduction

1.1 Background and motivation of research

Water is arguably the most essential resource for all life on the planet and has shaped human civilisations since the beginning of humankind. Since early hunters and gatherers realised the benefits of securing long-term supplies of fresh water for drinking and agriculture, a rudimentary form of water resources management (WRM) has existed. Modern WRM involves the planning, developing, distributing and managing of vital regional water resources and its mastery has been imperative to ensuring populations can grow and thrive.

For as long as water resources management has existed so too has the economic understanding of the value of water supplies. The Ancient Egyptians, knowing how crucial the spring floods were to the quality of the summer harvest, used the spring time water level in the river Nile to determine the amount of tax to charge the farmers that year. If the level was high they would tax more as the projected crops would be larger than usual (Popper, 1951). In contrast, an extremely low spring level in the Nile would indicate impending drought and, as a result, severe nationwide famine, rendering the taxation issue near arbitrary. Since the use of these early “nilometers”, all advanced civilisations have realised the importance of measuring and projecting water supply levels and the negative effects of an unmet demand.

Over the centuries, advances in engineering technology for the movement, storage and treatment of water has allowed city populations to grow to seemingly unlimited sizes. The downside however, is that these highly populated or heavily industrial/agricultural regions now rely on a constant uninterrupted supply of water, with potentially catastrophic consequences if disrupted. Modern day WRM approaches not only face the concerns of an uncertain rising global demand for water but also a widening range of uncertainty in how the natural climate will provide this water. Climate Change, as of 2016, is being viewed by leading scientific experts as the biggest potential threat to the global economy, and to water supplies, the world over (Environment Agency, 2013a; WEF, 2016). The World Economic Forum’s recent Global Risk Report (WEF, 2016) registered the two projected global risks of greatest concern over the next 10 years as ‘water crises’ and the ‘the failure of climate change mitigation and adaptation’, placing them above the likes of ‘weapons of mass destruction’ and ‘failure of national governance’. This risk assessment registered the increasingly high likelihood and high impact of these events and highlighted the importance of ensuring modern WRM adaptation approaches are fully prepared for the increasingly uncertain future ahead.

The central issue with current and traditional WRM practices, employed by most economically-advanced countries the world over, is that for years they have relied on the assumption that natural hydrology is relatively stationary (Kiang et al., 2011; Milly et al., 2008), inferring that the probability distribution of hydrologic events is unchanging over time. This has been an ideal assumption for water resource planners; as stationary hydrologic processes allow the use of statistical characterisation of the past behaviour of hydrologic variables to estimate the frequency of future events. However, the changing hydrological conditions, brought about by anthropogenic climate change, as well as concepts of multidecadal climate variability, presents a challenge to this long-lived assumption of stationarity.

It is highly likely that ongoing climate change will generate situations that have not been historically encountered. As a result, new WRM approaches must be implemented that can provide greater consideration of these future uncertainties and ensure an appropriate level of adaptation is prepared for all water resources systems at threat. The consequences of poor WRM adaptation planning range from an increase in undesirable restrictions on customer water use (via temporary use bans) through to complete system failure (i.e. a water shortage creating a social, environmental and economic disaster). However, the modern water resources planner must also maintain balance with investment; determining adequate resources are in place without overspending on expensive and potential unnecessary infrastructure.

To overcome these issues extensive international research is being carried out to test and evaluate a wide range of prospective methods for decision making under uncertainty, here termed decision making methods (DMMs), i.e. frameworks and approaches, which demonstrate notable potential in handling uncertainties, specifically “deep” uncertainties, in regard to WRM adaptive planning. In a WRM context, this denotes any method that can help a decision maker identify the “best” or “optimal” adaptation strategy(ies) to implement over a long-term planning horizon that accounts for uncertain increases or decreases in supply and demand attributed to uncertain levels of future climate change and population growth.

The research presented here is carried out as part of an Engineering Doctorate (EngD) project funded by the EPSRC under the STREAM Industrial Doctorate Centre and supported by HR Wallingford. Climate change adaptation is an increasingly important market sector for HR Wallingford. They have undertaken many consultancy studies relating to providing advice on climate change adaptation and recently have led the UK’s first climate change risk assessment (CCRA, 2012). With experience gained on these projects it has become increasingly apparent that there is currently no clear guidance on which decision making methods are most appropriate for these types of problems, especially in terms of evaluating practical demonstrations of their application on real-world complex WRM adaptation problems. This research aims to derive new knowledge providing clearer insight into the pros and cons of the different approaches (via qualitative and quantitative research); to identify existing knowledge gaps and ultimately help fill those gaps to assist in answering the water industries need to improve adaptation planning; to further develop some of the methods and quantitatively examine/define some of the more common but ambiguous terminology in WRM planning.

The terminology of particular interest is that of “resilience”. Numerous recent government and industry reports have highlighted the desire to increase system “resilience” in water resources management without clearly defining it; as stated by the World Economic Forum (WEF, 2016) in their future goals: “adaptation and resilience will be crucial to address the upcoming global challenges”; and by the UK Environment Agency (Environment Agency, 2013a): “(we need) to build resilience into the current water supply systems to drive economic growth and protect water bodies and to facilitate adaptation to the ever changing water supply, technological and social conditions”.

Given all of these issues, this research aims to investigate: the range of DMMs currently available for application to WRM; how they handle the uncertainties inherent to modern WRM problems; how they handle and quantitatively define key planning terminology and how their various contrasting key aspects can improve on current engineering practice.

1.2 Overall aim and objectives

The overall aim of this research is to compare and contrast a range of existing DMMs for possible application to WRM problems, critically analyse on real-life case studies their suitability for handling uncertainties relating to climate change and population growth and then use the knowledge generated this way to develop a new, resilience-based WRM planning methodology. This involves a critical evaluation of the advantages and disadvantages of a range of methods and metrics developed to improve on the existing EBSD methodology, to ultimately compile a list of suitable recommendations for a future framework for WRM adaptation planning under deep uncertainty.

The specific objectives of this research are as follows:

1. To undertake a critical review of a wide range of existing DMMs and related approaches. This review will identify and qualitatively evaluate DMMs that can be implemented to solve problems relating to decision making under uncertainty in the context of long-term water resources management, in particular associated with climate change adaptation, utilising an appropriate set of evaluation criteria.

2. To select a number of DMMs for WRM and perform their qualitative comparison. Based on the literature review, a number of promising DMMs will be analysed and compared using a set of criteria developed for this, all with the aim to short list a small number of most promising DMMs for further quantitative study in the context of WRM.

3. To develop a methodology for quantitative evaluation and comparison of selected DMMs for WRM. This methodology will start by defining in more detail the challenge of WRM under uncertainty to be analysed, followed by the definition of uncertain scenarios of supply and demand and a detailed

description of the DMM methods to be evaluated and compared. These methods (identified in objective 2) will be implemented in a software tool and if necessary/possible, further improved/customised in the process. An integral part of this methodology will be the definition and development of a dynamic water resources simulation model and tool that will be used for comparison on case studies. The software tool will be generic in a sense that it can be applied to various case studies, i.e. that it is capable of interacting with a range of water resources networks/system models.

4. To perform quantitative comparison of selected DMMs on real-life case studies. The selected DMMs for WRM under uncertainty will be evaluated and compared on real-life case studies / pilot sites based on real systems of regional water supply by using the objective 3 methodology. This will involve defining in detail suitable real-life case studies that will also be used for other work in the thesis. The results obtained will be examined to see if selected DMMs yield similar or markedly contrasting results, and in the latter case exploration of the reasons for the differences will take place. Recommendations will be made on the suitability of the methods tested for decision making under uncertainty given the climate change adaptation problem, with particular regard to their individual processes and underlining assumptions. Additional essential WRM adaptation planning aspects will be identified for further examination and investigative work, with particular regard to alternative performance metrics.

5. To investigate resilience aspects of adaptation planning in the context of water resources management. Important WRM adaptation planning aspects identified from objective 4 as warranting further research are examined more in-depth in order to complete an ensemble of recommended procedures for water resources adaptation planning under uncertainty. This includes an investigation of performance metrics in order to identify a suitable indicator to quantify water system resilience.

6. To develop a novel resilience-based methodology for optimal WRM under uncertainty combing optimal aspects derived from each stage of research. This method is then tested on an appropriate case study model produced as part of objective 4.

7. Consolidate a “minimum standard” list of aspects that should ideally be considered when approaching WRM adaptation problems under uncertainty in the future. The results obtained from all previous objectives are discussed and considerations for a future WRM framework in terms of potential “minimum” aspects of adaptation that should be considered when approaching WRM adaptation under uncertainty in the future are presented. Additional important planning aspects for improving adaptation will be also discussed.

8. Derive recommendations for further research. Conclusions are drawn from the results obtained and a WRM planning framework of the future discussed. Conclusions and further work is summarised as well as discussion on additional key planning techniques, from engineering solutions to hybrid decision methods that could be essential for insuring an appropriate level of future adaptation is implemented in the water industry, both in the UK and internationally.

1.3 Thesis Structure

This thesis contains nine chapters including this introductory chapter. An overview of the nine chapters is given below in Table 1.1, including a list of all published journal or conference papers relating to the respective chapters. A full list of publications produced during this study is given below Table 1.1.

Table 1.1: Outline of thesis chapters

Objective addressed	***Overview of chapter***	***Related papers***
Objective 1	***Chapter 2**: This chapter provides an overview of the core topics and most pertinent research literature related to this study in order to frame the research objectives and justify the work carried out within this thesis. It addresses objective 1 by reviewing a wide range of potential methods and approaches for decision making under uncertainty, then shortlisting key DMMs for a more in-depth qualitative review, including the selection of a suitable set of criteria for evaluating/reviewing the various methods. This qualitative review is then carried out in Chapter 3.*	
Objective 2	***Chapter 3**: This chapter is structured as a comparative qualitative assessment of the most promising DMMs identified based on a detailed literature review presented in Chapter 2. The methods are reviewed using a set of criteria developed for this purpose in order to identify key DMMs for further quantitative assessment in Chapters 4 and 5.*	
Objective 3	***Chapter 4:** This chapter introduces the methodology for the quantitative evaluation and comparison of two DMMs selected in Chapter 3. It details the WRM under uncertainty problem analysed, the dynamic water resources simulation model developed, the uncertain scenarios of supply and demand and provides a detailed description of the two DMMs analysed (IG and RO methods).*	

Objective addressed	Overview of chapter	Related papers
Objective 4	***Chapter 5**: This chapter presents two real-world WRM case studies (Sussex North and Bristol Water). The selected DMMs are then applied to these case studies using the methodology described in Chapter 4 in order to analyse the issues highlighted in Chapter 3. The in-depth examination of the DMMs on the case studies results in recommendations for further investigative work addressed by objective 5.*	*Section 5.3: Case study 1. Journal paper (Roach et al., 2016b) published by J. Water Resour. Plann. Manage; Conference paper (Roach et al., 2014) published by CUNY Academic Works.* *Section 5.4: Case study 2. Conference paper (Roach et al., 2015a) published by Procedia Engineering.*
Objective 5	***Chapter** 6: In this chapter an investigation is carried out on a group of newly developed performance metrics that could be utilised to quantitatively define resilience in future water resources adaptation guidelines. This performs a more in-depth examination of aspects identified from Chapter 5 as warranting further research and completes an ensemble of recommended procedures for WRM adaptation planning under uncertainty, addressing objective 7.*	*Conference abstract and presentation (Roach et al., 2015b) published in book of abstracts by Deltares Research Institute from the Third Annual Workshop on Decision Making Under Deep Uncertainty*
Objective 6	***Chapter 7**: This chapter presents a novel resilience-based methodology for optimal water resources planning utilising key processes highlighted from the previous chapters and the optimal resilience metric derived from Chapter 6 to address objective 6. The optimal adaptation strategy results are then compared with results produced using a 'current practice' methodology.*	*Journal paper (Roach et al., 2016a) under review by Water Resour. Res.*

Objective addressed	*Overview of chapter*	*Related papers*
Objective 7	***Chapter 8****: This chapter discusses the relative importance of the various metrics and methods investigated, presenting a potential "minimum standard" of aspects of adaptation that should be considered when approaching WRM adaptation problems under uncertainty in the future. Additional important planning aspects for improving adaptation are also discussed.*	
Objective 8	***Chapter 9****: This chapter summarises the conclusions of each chapter and discusses their significance and limitations, including recommendations for further research.*	

Papers presented by the candidate:

Roach, T., Kapelan, Z., Ledbetter, M., Gouldby, B., and Ledbetter, R. (2014). Evaluation of decision making methods for integrated water resource management under uncertainty. *CUNY Academic Works*. http://academicworks.cuny.edu/cc_conf_hic/58

Roach, T., Kapelan, Z., and Ledbetter, R. (2015a). Comparison of info-gap and robust optimisation methods for integrated water resource management under severe uncertainty. *Procedia Engineering*, 119, 874–883.

Roach, T., Kapelan, Z., and Ledbetter, R. (2015b). Evaluating the resilience and robustness paradigms for water resource systems adaptation. *Third Annual Workshop on Decision Making Under Deep Uncertainty*. Deltares, Delft.

Roach, T., Kapelan, Z., and Ledbetter, R. (2016a). A comparative assessment of a resilience-based methodology for optimal water resource adaptation planning under deep uncertainty against conventional engineering practice in the UK. *Water Resour. Res.* (Under Review).

Roach, T., Kapelan, Z., Ledbetter, R., and Ledbetter, M. (2016b). Comparison of robust optimization and info-gap methods for water resource management under deep uncertainty*. J. Water Resour. Plann. Manage.*, 04016028.

Chapter 2. Literature Review

2.1 Introduction

This chapter provides an overview of the core topics and most pertinent research literature related to this study in order to identify the current state-of-the-art in the field and justify the work carried out within this thesis. The literature review is split into five distinct sections:

(1) Section 2.2 – Overview of water resources management (WRM) problem.
(2) Section 2.3 – The history, evolution and current practice of WRM in the UK (with references to international similarities/variations), highlighting the timeliness and necessity of the research.
(3) Section 2.4 – The projected future uncertainties, namely increasing climate change and urbanisation effects and their projected impacts on current planning approaches.
(4) Section 2.5 – Definitions of key terminology utilised throughout this study including discussion of specific metrics and examples of their use in recent literature.
(5) Section 2.6 – Typical and emerging approaches for WRM planning under uncertainty, leading to a full qualitative review of some of the most prominent decision making methods being promoted for use in the water industry (Chapter 3).

The literature study and follow-on qualitative review in Chapter 3 aims to detail the core subject information for WRM planning under uncertainty, identify the current knowledge gaps in the science and thus identify matters of further research interest. The qualitative findings detailed (see section 3.5) then substantiate the selection of quantitative work carried out in Chapters 4-7.

2.2 Overview of water resource management (WRM) problem

Water resources management (WRM) systems worldwide have undergone a series of significant evolutions over the past century. Advancements in the treatment and supply of clean potable water as well as the hygienic removal and treatment of wastewater have been responsible for reducing worldwide disease and facilitating an increase in agriculture, industries and populations whilst simultaneously improving life expectancy and the quality of life for billions of people across the planet (Sultana, 2013). Water is, in many regards, the world's most precious resource (Defra, 2011a). The advancements in water engineering technologies have allowed populations to rise across the planet, even in arid regions, such as in the Middle East, where processes such as seawater desalination have provided substantial water supplies in regions that frequently go extended periods without significant rainfall (Dawoud, 2005). However, improvements in technology have been partnered with an increase in man-made atmospheric pollution, most notably the rising emissions of carbon dioxide and methane levels into the Earth's troposphere from large scale modern industry and agriculture (Lu et al., 2007; Stevenson et al., 2000). This has led to increasingly significant levels of climate change and with it, rapidly growing uncertainties in the behaviour and reliability of many regional sources of water supply. This combined with increased urbanisation and rapidly growing regional populations is putting pressures on finite water resources (Environment Agency, 2013a). Water companies and utilities worldwide are now under pressure to modernise their management frameworks and approaches to decision making in order to identify more sustainable and cost-effective water management adaptations that are reliable in the face of uncertainty.

2.3 The history, evolution and current practice of WRM (in the UK)

The real-life case study work examined in the later chapters of this thesis are all situated in the UK and explore comparisons with current UK industry practice. In order to facilitate this later examination, and understand the issues of present day WRM, a review of the history, evolution and current practice of WRM in the UK is conducted first.

2.3.1 WRM in the UK (1940-1980)

Water management, from the management of water resources and supply of water, to the control of flooding and the treatment of sewage, was largely an uncoordinated activity around the globe until the second half of the twentieth century (Ofwat, 2006). Prior to this water management was a highly fragmented and localised activity. For example, over 1,000 individual rudimentary bodies were involved in the supply of regional clean water in England and Wales alone in 1945 and over 1,400 separate bodies were operating to control sewerage. Following the end of the Second World War the focus of government legislation within the UK water industry was to consolidate the local authorities to enable each supplier to profit from improved arrangements for the shared supply of resources across regional bodies (Ofwat, 2006). Post-war rising populations and a boom in both industry and agriculture, coupled with largely unregulated abstractions and use of water resources, led to multiple drought events occurring in the late 50's with a particularly severe national drought occurring in 1959 (Marsh et al., 2007). This was in turn followed by devastating flooding events in 1960 prompting the formation of The Water Resources Act 1963 (HMSO, 1963). The act introduced water abstraction permits and a fully administrative system approach for water resource planning, recognising the benefits of a co-ordinated approach to management. This was advanced to the Water Act 1973 (HMSO, 1973), which established 10 new regional water authorities that would manage both water resources and sewerage services on a fully integrated basis. This act set in place a cost-recovery system whereby each new water authority would borrow investment capital from the government, which in turn would be paid back by revenue from the services provided. However, due to instabilities in the economy and growing debts in the water authorities this led to largely insufficient annual expenditure occurring in both system maintenance and investment throughout the 1970s and 1980s.

2.3.2 WRM in the UK (1980-2015)

In response to growing debts an updated Water Act was brought out in 1983 (HMSO, 1983). This led to significant constitutional changes reducing the role of local government in decision making in the water industry and opening the door to private capital markets, advancing to full privatisation of the water industry in 1989 (HMSO, 1989). Privatisation involved the transfer of all assets and personnel of the 10 water authorities (previously managed by the government) over to private limited companies. This triggered an immediate boost in capital investment cash as the newly formed national water companies were floated on the stock exchange in a one-off public capital injection process. In order to ensure rising pollution threats were managed and new national/European legislations were upheld a further restructuring was performed. This involved the establishment of three independent controlling bodies to regulate the activities of the new water companies in both clean water supply and sewerage control within the UK. These were: the National Rivers Authority (now succeeded by the Environment Agency (EA)), acting as the environmental regulator; the Drinking Water Inspectorate (DWI – a sector of the Department for Environment, Food and Rural Affairs (Defra)), acting as the water quality and policy regulator, and the Office of Water Services (Ofwat), acting as the economic regulator.

The turn of the millennium also saw several European directives issued to all member states of the European Union (EU) including the 'Water Framework Directive' (European Union, 2000), which required all EU water bodies to reach a 'good status' over time and provided a framework of how to reach this specific standard. Further UK water acts; from the Water Act 2003 (HMSO, 2003) through to the Water Act 2014 (HMSO, 2014), have continued to tighten regulations on the water companies and improve planning and inter-regional cooperation.

2.3.3 WRM in the UK (2016 and beyond)

As of 2016 there are currently 12 water companies operating in the UK that handle water supply and sewerage across wide regions and several smaller "water-only" companies existing to provide water to local cities/communities or regions segregated from the major companies. Since the formation of the independent water companies substantial improvements have been made to the quality of drinking water, rivers and bathing water as well as attracting over £108 Billion in investments to meet rising demands and environmental/treatment obligations (Ofwat, 2016). The increased capital and operational funding has led to an industry that is far more efficient then pre-privatisation times. However, the rise in investment is induced by rising customer bills that have seen a steady increase since privatisation was first established. Substantial improvements in data quality have allowed companies to target their expenditure where it is most needed, however all investment decisions require significant validity and proof of requirement in order to be accepted by the regulators.

Recent Water Acts (HMSO, 2014; 2016) have further improved the regulatory boards and encouraged competition of performance between the companies in order to continue to deliver more efficient and stable services, especially in light of the latest significant challenge; rising uncertainties. The most recent Water Act (HMSO, 2016) also acknowledged these rising uncertainty issues by calling for a combining of company water resources management plans (WRMPs) with their company drought plans in the future in order to syndicate these two important facets of WRM adaptation planning. The rising uncertainties, especially those exacerbated by climate change effects and population growth, have been highlighted in recent government reports as ‘the’ growing threat to the efficient planning and operation of UK and world-wide water systems (Defra, 2009, 2011b; 2013; Environment Agency et al., 2012; Environment Agency, 2013a; HMSO, 2014). Water UK's (2016) report on the long term water resources planning framework highlighted these threats further and examined the case for adopting a consistent national minimum level of resilience and taking a more national view on water resources, future climate change and drought risk. The water industries, both UK based and international, must now continue their tradition of evolution and innovation within their management frameworks and planning approaches, if water companies and national water services are to ensure stable and affordable water supplies and sewerage services in a future of rising uncertainties.

2.3.4 Current WRM planning approaches (UK and international)

Water management regulatory frameworks differ around the world but in many countries similar plans are developed under the auspices of Integrated Water Resources Management (IWRM) or simply WRM programmes. For instance, water utilities in the UK are required to produce Water Resources Management Plans (WRMPs) every five years that outline their long-term strategies for maintaining a secure water supply to meet anticipated demand levels. These plans justify any new demand management or water supply infrastructure needed and validate management decisions (Environment Agency et al., 2012). Similar WRM planning is fostered around the world as recommended by the

Global Water Partnership (GWP) with the vision of a water secure world (Falkenmark and Folke, 2000), including increasing regard given to sustainable water planning and policy in developing countries (Bjrklund, 2001). Modern day WRM planning is a multi-objective problem where decision makers are required to develop strategic *adaptation* plans to maximise the security of water supplies to future multiple uncertainties, whilst minimising costs, resource usage, energy requirements and environmental impact (Charlton and Arnell, 2011; Environment Agency, 2013a).

The projected increases in climate change have lead governments and water industries worldwide to question the suitability of their current managerial approaches to water resources management. Recent WRM case studies in highly water stressed regions, including: Vietnam (Khoi and Suetsugi, 2012), Indonesia (Santikayasa et al., 2015), Turkey (Fujihara et al., 2008), South Korea (Bae et al., 2008), India (Narsimlu et al., 2013), Australia (Keremane, 2015; WSAA, 2012), Kenya (Mango et al., 2011), Bhutan (Chhopel et al., 2011), Mexico (Oswald Spring, 2015), South Africa (Mukheibir, 2008), the United Arab Emirates (Murad, 2010), California in the US (Purkey et al., 2007) and studies in the developing world (Adger et al., 2003; UNFCCC, 2007), have all projected high levels of climate change uncertainty, potentially disastrous future scenarios and have highlighted the weaknesses in the outputs of current approaches when a wider range of uncertainty is considered. This has led to the generally resounding international recommendation of advancing current WRM practices and/or policies and providing more data and computational tools to aid water resource planners in preparing for an uncertain future.

The current water supply planning approach in the UK is to ensure a regional water system maintains a designated “level of service” to its customers, as stated in the Environment Agency’s (EAs) Water Resources Planning Guideline (WRPG) for England and Wales (Environment Agency et al., 2012) and the Economics of Balancing Supply and Demand (EBSD) (NERA, 2002). The term “level of service” is essentially an agreement between a water company and its customers describing the average *frequency* that a company will implement temporary restrictions on water use. A water system is designed to never reach a point of complete water shortage (i.e. an unfulfilled demand or complete system failure); however, a company is anticipated to occasionally introduce temporary water restrictions, such as temporary use bans to manage water demand during periods of drought. However, this “level of service” calculation lacks transparency and is often presented as a general target (e.g. a target system performance of no more than 1 in 10 or 1 in 15 years enforced restrictions (Bristol Water, 2014; Southern Water, 2014)). It is also calculated irrespective of the duration of each projected restriction. Further to this it relies on an assumption that a drought event can be assigned a probability of occurrence and associated return period which are known to be poorly understood and misrepresentative for drought events (Turner et al., 2014a). Especially in light of increasing climate change effects where the impacts on hydrology are likely to be non-linear and felt most at the extremes (Allen and Ingram, 2002).

The EBSD approach is to produce a “best estimate” of future deployable output (or system yield) for a given water resources network. Using climate change projections and regional population forecasts, the aim is then to deliver an acceptable (i.e. target) “level of service” for the least cost given the projected changes in supply and demand. This produces a single best estimate of the future supply-demand balance over time and encourages a “predict and provide” type approach to WRM over a single projected future or pathway (Lempert and Groves, 2010). Target Headroom (Environment Agency et al., 2012) is then added as a “safety margin”, defined as “the minimum buffer that a prudent water company should allow between supply and demand to cater for specified uncertainties in the overall supply-demand resource balance” (UKWIR, 1998) and is calculated by applying probability density functions (pdfs) to all sources of uncertainty in supply and demand (Hall et al., 2012b).

The current EBSD approach does not fully explore the wider range of possible futures, the so called “*deep*” uncertainties (Walker et al., 2013b), or the full range of potential solutions and trade-offs. Nor does it promote examination and security against the more extreme projected scenarios; such as severe changes in individual supply source availability at peak demand periods (Environment Agency et al., 2012) or highly unexpected events (the so called black swans) (Bryant and Lempert, 2010). It does not encourage the most *robust* or *flexible* strategies to be derived, but instead satisfies a single projected supply-demand balance over a short timescale of 25 years.

A recent revised and updated guidance report by UKWIR (2016a) has outlined a range of feasible techniques for improving on the current decision making framework; however, the current EBSD approach still remains the benchmark methodology for water resource planners. The report indicates that industry methods are ready to evolve; however, the level of modelling complexity and the choice of decision tools utilised are left open to planner preference and are currently designated as non-compulsory ‘extended’ additions to traditional adaptation planning.

The current UK water industry is also plagued by conservative decision-making (Gober, 2013). Companies are averse to public scrutiny and gauge success by the absence of public debate and public attention. This favours small infrastructure solutions and a strategy of low cost “maintenance” over larger scale “robustness”. It is also understandable for governments and authorities to delay on making very costly strategic adaptation decision when there are significant uncertainties to the level of predicted adaptation required, i.e. the need to avoid further “white elephants” in the water industry is paramount (Hansard, 2009). A decision is very difficult to make when the very parameters of the problem are uncertain and especially as the climate and resulting weather, with all its pressure changes, temperature differentials, wind speeds, jet streams, moisture contents, oceanic gas absorption, cyclic variables, and unexpected accumulation of cloudy fronts, is in itself, extremely unpredictable. However, in the words of John Quiggin, noted Economist and fellow of the Australian Research Council Federation, “either way, uncertainty about the future does not justify inaction in the present” (Quiggin, 2008). Especially relevant when overwhelming scientific data projects us towards future scenarios where inaction, both in mitigation and adaptation, could prove very costly if not catastrophic. Particularly for countries situated in the northern tropics where future climate change induced water stresses are projected at their most prolific (IPCC, 2007a).

2.4 Key future uncertainties for WRM

2.4.1 Future supply uncertainties

Current water management systems work under the assumption that natural systems fluctuate within an unchanged envelope of variability (Milly et al., 2008). That is to say the probability distribution of hydrologic events is unchanging over time and that any hydrologic variable (e.g. the peak flow rates of a river etc.) has a time-invariant and 1 year periodic probability density function (pdf – a likelihood measurement), whose property can be estimated within some level of accuracy from accurate instrument records (Kiang et al., 2011). The estimate errors in probability density functions are acknowledged but are assumed to be easily reducible by additional time observations, i.e. patterns in the climate will generally repeat and can be estimated within an acceptable level of error. However, substantial anthropogenic change of the Earth's climate is modifying patterns of rainfall, river flow, glacial melt and groundwater recharge rates across the planet, undermining many of the stationarity assumptions upon which water resources infrastructure has been historically managed (IPCC, 2007b). This is creating a potentially vast range of possible climate futures that could threaten the reliability of vital regional water supplies across the planet.

Current planetary global warming and climate change is primarily attributed to increasing emissions of CO_2 and other greenhouse gases into the Earth's atmosphere from anthropogenic sources, particularly the burning of fossil fuels and deforestation (Etheridge et al., 1996). Multiple lines of scientific evidence show that Earth's climate system is warming (EPA, 2013; Hartmann et al., 2013). This warming effect is anticipated to lead to large reductions in the world's cryosphere (Fitzharris et al., 1996; IPCC, 2007a), leading to rising sea levels, changing precipitation patterns and an expansion of deserts and subtropics (Lu et al., 2007). Other projected changes include more frequent extreme weather events worldwide, such as heat waves, droughts, severe snowfall and heavy rainfall with floods (Held and Soden, 2006). Although warming effects, such as increased glacial melt-water, does temporarily enhance water availability in mountainous regions it eventually diminishes all nearby natural storage levels as snow-pack losses are not being replaced

(Barnett et al., 2005). Expansion of the subtropical dry zone (desertification) and an increase in humidity related precipitation encourages the drought-flood reflex of the planet and means water companies need to be more prepared for increased bouts of both. A number of global surface water sources, including regions in the southern UK, are predicted to diminish in output over the coming century, particularly in the sun intensive equatorial and northern tropic regions of North Africa, Southern Europe, Central America and Central Asia, regions often already suffering from severe water stresses (IPCC, 2007b).

The year 2015 has seen numerous weather records broken, which include; the highest level of ocean warming on record, the most extensive melting of winter sea ice in the Arctic, an unprecedented killer heat wave in South Asia and several heat records broken across Europe (WMO, 2016). The global average surface temperature in 2015 broke all previous records by a wide margin, at about 0.76° Celsius above the 1961-1990 average because of a powerful El Niño combined with human-caused global warming. The record breaking trend has continued into 2016 and new heat records are already being set, with average global air temperatures for January, February and March being the highest recorded for those months (WMO, 2016).

Despite numerous worldwide mitigation efforts, a certain amount of continued climate change is now unavoidable and requires timely adaptation decisions in water resources management. However, projections of local climate change impacts are plagued with substantial uncertainties, making supply projections, and anticipatory adaptation, extremely difficult. As the climate is shifting across the planet, so too are stream flows, the frequency and duration of extreme events, and as such, the practice of water modelling and management (Lins and Cohn, 2011; Milly et al., 2008). Traditional methods for assessing expected climate change typically work on the use of three climate scenarios, “low”, “mid” and “high”, sometimes written as “dry”, “mid” and “wet”, based on data from six different global circulation models (GCMs) often termed as global climate models (Environment Agency et al., 2012; IPCC, 2007b). These three scenarios typically represent the mean projections as well as the 5th and 95th percentile extreme projections. This allows triangular distributions to be created from the averages to the extremes in order to represent the scale of uncertainty. However, due to weaknesses in the catchment and groundwater models, this method when applied to water resources management decisions is largely reduced to a less reliable single estimate “factoring” method. The extremes are considered allowable if only occurring for brief periods (extreme droughts etc., which can be managed should they arise for a short time) and so management plans are often made in accordance to the mean estimate of climate change manipulated to varying levels throughout the different seasonal periods. This has proven reliable enough in the past but is now recognised as no longer being sufficient to cope with the more irregular projected future changes in the hydrological systems (Milly et al., 2008). In UK Water Industry Research (UKWIR) (1997) the use of factoring historic data to project river flows etc. was viewed as a short-term response to the lack of catchment hydrological models. However, many years later, “flow factors” are still the most widely used approach for climate change consideration in water resources management plans.

2.4.2 Future demand uncertainties

The growing non-stationarity of hydrological variables affecting water supply projections is also being replicated in the demand side of projections. Increased urbanisation and accelerated population growth are the main contributing factors, however changes in land use, water use and unpredictable weather/climate change are all drivers that bring about non-stationarity to the water demands of a region (Kiang et al., 2011). This combination of drivers is increasing demand uncertainties and making it difficult for water companies to form reliable long term projections. The Office for National Statistics (ONS) forecasts population growth for England and Wales of between 6 and 16 million by 2040, and between 12 and 32 million by 2065 (ONS, 2014a), marking population growth as one of the largest uncertainties in the future supply/demand balance.

Larger populations increase the demands on individual water resources and growing populations in vulnerable areas means floods and droughts are becoming far more commonplace and far more expensive and disruptive. If demand projections are significantly misjudged or modelers lack sufficient foresight to incorporate potential prolonged periods of high demand, and/or potential threats and interruptions to supplies, then highly populated regions could suffer severe and prolonged periods of water stress, which can be socially and ecologically damaging and, at worst, potentially life threatening. Factors that need to be considered include the possible increases in household and non-household demands due to population growth, population migration, agricultural and industrial increases, and the changes in general individual requirements, especially in the developing world (Environment Agency et al., 2012). Demand uncertainties would also include the potential changes in leakage levels as leakage should be considered as an outgoing factor, as water supply is being consumed by the leak. Climate change also impacts directly on water demand, hotter temperatures will increase demand for water, both in domestic use and, most significantly, in agricultural use, as enhanced irrigation will be required. Although these are small compared with the climate change impacts on supply (UKWIR, 2012).

2.5 Definitions of key terminology in WRM adaptation planning

Before new and emerging planning methodologies/approaches are discussed it is important to first clarify the explicit WRM adaptation problem being solved here and establish the definition of several key terms in WRM adaptation planning.

2.5.1 WRM Problem definition

The WRM adaptation problem being solved here is defined as the long-term water resources planning problem of ensuring a regional water supply system meets future demand. The solution/aim is to, for a given long-term planning horizon (typically 25 years used in current UK water industry practice), determine the best adaptation strategy(ies) (i.e. set of interventions scheduled across the planning horizon) that are required to upgrade the existing water resources system so that it maintains a target level of system performance over a range of uncertain future conditions/scenarios. The term decision making methods, i.e. the methods that can be applied to solve this WRM problem, are now explained below, including a more detailed explanation of adaptation strategies, deep uncertainties, scenarios, robustness and other important pieces of terminology explored within this study.

2.5.2 Decision Making Methods (DMMs)

To overcome the issues mentioned in sections 2.3 and 2.4 extensive international research is being carried out to test and evaluate a wide range of prospective Decision Making Methods (DMMs), i.e. frameworks and approaches, which demonstrate notable potential in handling uncertainties, specifically “deep” uncertainties (see section 2.5.3), in regard to WRM adaptive planning. A DMM, in a WRM context, denotes any method that helps a decision maker identify the “best” adaptation strategy(ies) (see section 2.5.4) over a long term planning horizon that are either automatically generated or selected from a range of pre-defined solutions. Section 2.6 gives a thorough review of existing and potential DMMs for application to WRM adaptation problems.

2.5.3 Deep uncertainty

One of the greatest challenges facing decision makers in the UK water industry are the increasing influences of “deep” climate change, population growth and urbanisation uncertainties affecting the long-term balance of supply and demand and necessitating the need for adaptive action (Charlton and Arnell, 2011; Environment Agency, 2013a). As a consequence the above uncertainties are now widely acknowledged but it is important to be clear on the definition of uncertainty. Knight (1921) was the first to distinguish between risk and uncertainty, declaring uncertainty as the risks that were incalculable and uncontrollable. Deep uncertainty has since evolved from this concept to encompass all uncertainties where no specific level of probability can be attached (Lempert et al., 2003; Morgan and Henrion, 1990; Quade, 1989). Lempert et al., (2003) defines a condition of “deep” uncertainty as one in which the parties to a decision do not know or cannot agree on the system models relating actions to consequences, or on the prior probability distributions for the key input parameters to those models. Walker et al. (2013b) simplifies this to define the point at which uncertainties become “deep” as when one can enumerate multiple plausible alternatives of the future but cannot rank the alternatives in terms of perceived likelihood.

Under Walker’s definition uncertainties are often categorised by the generation of multiple future scenarios that represent alternative plausible conditions under different assumptions (Mahmoud et al., 2009). Combining these scenarios with a suitable metric to measure system sensitivity to changing conditions (i.e. robustness) can then facilitate the examination of the potential benefits of alternative system configurations (i.e. adaptation strategies) across a range of deep uncertainties. The interaction of deep uncertainty, scenarios, robustness and adaptation is discussed in detail by Maier et al. (2016).

"Deep" uncertainty is also well known under a number of other guises including, but not limited to: "strict", "severe", "extreme", "wild", "vast", "true" or even "Knightian" uncertainty (Knight, 1921). However the most predominant term "deep" will be used throughout this study.

2.5.4 Adaptation strategy

Any change in a natural environment will cause consequential changes to the organisms living in that environment. That change comes in the form of an adaptation mechanism, where a species adopts new processes and procedures to cope with its new surroundings. Adaptation strategies are so named in this context and denote a set of procedures to ensure a water system can cope with a projected single, or array of, future event(s). Thus in this study an adaptation strategy is defined as a set of intervention options (such as options to provide additional water resources, or options to reduce water losses or consumption) scheduled across a planning horizon that are required to upgrade an existing regional water resources system to satisfy a range of deep uncertainties and multiple objectives.

2.5.5 Future scenarios (of supply and demand)

Scenarios are possible future states of the world that represent alternative plausible conditions under different assumptions (Mahmoud et al., 2009). They are defined by the IPCC (2008) as; ''a coherent, internally consistent and plausible description of a possible future state of the world. It is not a forecast; rather, each scenario is one alternative image of how the future can unfold". As illustrated by the conceptual "scenario funnel" in Figure 2.1, scenarios provide a dynamic view of future uncertainties by exploring various trajectories of change and system disruption leading to a broad range of plausible alternative futures.

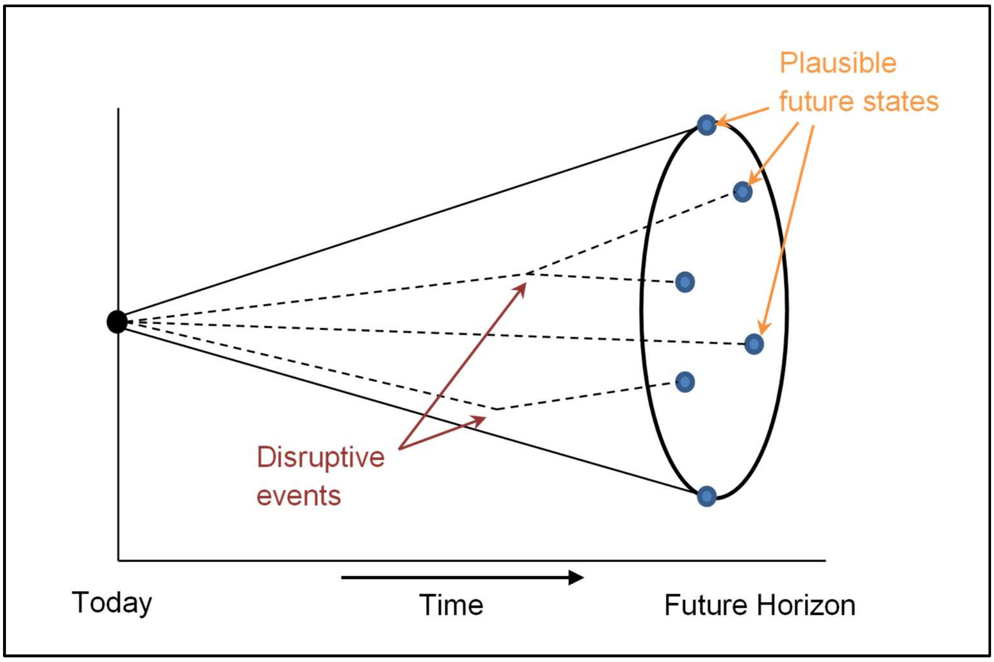

Figure 2.1: The "scenario funnel" – conceptual drawing. Adapted from Timpe and Scheeper (2003)

Scenarios describe an entire sequence of events over a given planning horizon and should not be confused with a sensitivity analysis (e.g. Demaria et al., 2007; Tang et al., 2007), which examines how changes in a single specific factor or parameter (e.g. temperature, precipitation rate etc.) can affect the output of a specific water resource. Scenarios are considered better suited for modern day planning and management of complex systems due to their ability to challenge conventional thinking and accepted assumptions when producing possible futures (Mahmoud et al., 2009). When developing scenarios, the objective is to produce a small collection of vastly different but still highly plausible futures of a whole range of system factors, whereas a sensitivity analysis tends to produce a large number of simulations following gradual variations in one single factor.

The main disadvantage of using scenarios is in a probabilistic manner in that it can become difficult to assign a likelihood to a set of fluctuating and complex changing conditions, in turn making it difficult to assign a level of probability to such an uncertain set of outcomes (Mason, 1998). However, this issue is easily reducible when dealing with "deep" uncertainties as a level of likelihood generally becomes un-assignable (Walker et al., 2013b). Utilising likelihood assumptions will also heavily weight, and thus generally favour, strategies that design to the "most-likely" conditions, which cause the more unexpected future events to be ignored (a drawback of current engineering practice) and encourage the selection of a less "overall" robust system. For this reason a wide range of plausible supply and demand scenarios deemed "equally likely" have been generated for this study.

There are various state-of-the art methods for producing supply scenarios to represent alternative plausible future conditions of a system. Mahmoud et al., (2009) broke-down the various methods into a tree of scenario types (Figure 2.2).

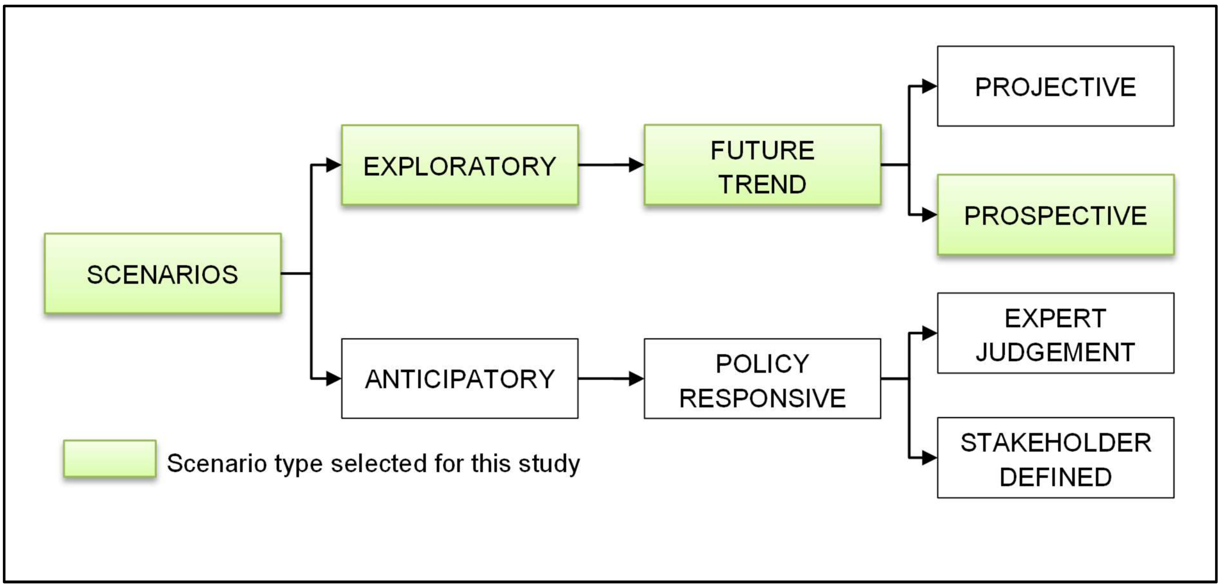

Figure 2.2: Tree of main scenario types found in literature. Adapted from Mahmoud et al. (2009)

Exploratory future trend scenarios are based on extrapolation and alteration of past trends and patterns and either project forward in time using trends experienced in the past (*projective*) or anticipate upcoming change and apply significant variations to past trends (*prospective*). Anticipatory policy responsive scenarios are based on planning for critical issues identified by either expert decision makers within water resources management (*expert judgement*) or by relevant stakeholder needs (*stakeholder defined*). Anticipatory scenarios tend to be highly subjective and may contain bias towards particular scenarios that benefit companies and stakeholders (Hulse et al., 2004; IPCC, 2007a). *Projective* scenarios were commonly used in historic planning methods when climate stationarity was an accepted assumption (Hulse et al., 2004; Milly et al., 2008); however, their simplicity does not permit the identification of all potential futures under rising uncertainties. For these reasons a *prospective* scenario type is more suitable for problems under “deep” uncertainty and is therefore the scenario type selected for later quantitative work in this study (see Figure 2.2). Under this approach future supply scenarios can be generated utilising plausible climate projections combined with randomised variations in the timing and frequency of future drought periods in order to produce a wide array of different scenarios that avoid directly copying historic patterns of events.

2.5.6 Robustness

Robustness has many definitions. In general systems analysis it refers to the ability of a system to tolerate perturbations and changes without adapting its initial stable configuration (Wieland and Wallenburg, 2014), or in computer science as the degree to which a system or component can function correctly in the presence of invalid inputs or stressful environmental conditions (IEEE, 1990) and in biological science as the persistence of a certain characteristic or trait in a system under perturbations or conditions of uncertainty (Félix and Wagner, 2008).

Robustness is commonly described in WRM literature as the degree to which a water supply system performs at a satisfactory level across a broad range of plausible future conditions or scenarios (Groves et al., 2008; Matrosov et al., 2013; Moody and Brown, 2013). Alternative definitions of system robustness have been discussed in recent WRM literature that branch away from the common satisficing calculations, including regret-based measures and sensitivity controls (Herman et al., 2015), exploratory modelling and analysis (Kwakkel and Pruyt, 2013), applied forms of Maximin or Minimax theory (Giuliani and Castelletti, 2016) and alternative satisficing practices incorporating decision scaling and Monte Carlo analysis (Asefa et al., 2014; Steinschneider et al., 2015). In the quantitative assessment work carried out in Chapters 4-7 robustness of long-term water supply is specifically defined as the fraction (i.e. percentage) of future supply and demand scenarios that result in an acceptable system performance, as it elicits a transparent quantified calculation of robustness that is suitable when examining a wide range of highly variable discrete future scenarios and has been successfully employed in numerous recent WRM studies (Beh et al., 2015a; Herman et al., 2014; Paton et al., 2014a; 2014b).

Numerous individual and comparative DMM studies have been conducted within the context of WRM adaptive planning with specific attention to a measure of *robustness* (Ghile et al., 2014; Haasnoot et al., 2013; Jeuland and Whittington, 2014; Kwakkel et al., 2015; Lempert and Groves, 2010; Li et al., 2009; Moody and Brown, 2013; Paton et al., 2014a; Tingstad et al., 2014; Turner et al., 2014b; Whateley et al., 2014). Walker et al., (2013a) produced a review of conceptual approaches for handling deep uncertainties and concluded that further work needed to be done on the systematic comparison of approaches and computational tools for handling *robust* planning to better derive the potential strengths and weaknesses of the various approaches.

2.5.7 Performance metrics – resilience, reliability and vulnerability

Where the term “robustness” defines the performance of a water system across a broad range of future conditions, a performance metric (or indicator/criterion) defines the performance of a system to a single future scenario or set of conditions. The more well-known performance metrics often cited within WRM literature are those of Hashimoto et al. (1982) who were among the first to propose the use of the terms; reliability, vulnerability and resilience for water resource system performance evaluation. These performance criteria, in general, refer to how likely a system is to fail (its reliability), how severe the consequences of failure might be (its vulnerability) and how quickly it can bounce back, which is the recovery from a failure (its resilience). The EBSD ‘levels of service’ method used in current UK engineering practice can be most closely equated to a performance criterion of reliability, as it’s the likelihood of temporary restrictions being enforced that describes the ‘level of service’. The vulnerability of the system is also implicitly included in the control rules and triggers used to define each ‘level of service’ event for a given resource system, however current practice does not explicitly consider the resilience of the system. For instance, a water system may be projected to maintain its target reliability level of a 1 in 15 year probability of water deficit occurring, however this assessment does not explore the length of time these deficit periods may last. A prolonged single water deficit period may be as detrimental to the system and its customers as a higher frequency of smaller deficit periods. However, the latest investigation by the EA into water resources planning methods of the future (Environment Agency, 2013a), called for a review of the EBSD ‘levels of service’ method and for the advancement of incorporating more *resilience* into water resources system planning, indicating it will support adaptation strategies that are aimed at improving system resilience. Recent UK government reports (Defra, 2011b; 2016a; Water UK, 2016) have recognised the importance of system resilience and highlighted the desire to increase it in water resources management. However, there is still no quantitative definition of resilience (Environment Agency, 2013a) and resilience remains generally poorly defined in practice to date.

The application of resilience as a criterion for measuring the performance of a water resources or water distribution system has been explored (Jung, 2013; Linkov et al., 2014). Lansey (2012) defined resilience as a system’s ability to “gracefully degrade and subsequently recover from” a failure event. Holling (1986) defines resilience as the ability of a system to return to an equilibrium or steady-state after a disturbance, to absorb shocks but still maintain function. Ofwat’s Resilience Task and Finish Group (Ofwat, 2015) recently defined resilience as “the ability to cope with, and recover from, disruption, and anticipate trends and variability in order to maintain services for people and protect the natural environment now and in the future". For WRM, resilience has generally been quantified as the duration of time (maximum or average) temporary restrictions are in place due to low supply availability; although its calculation is highly varied throughout the literature. Several examples of resilience being used as a performance criterion/metric include Matrosov et al., (2012) and Paton et al., (2014a) who calculated resilience as the average duration of time a system is under a temporary restriction. Fowler et al., (2003) calculated it as a fraction of the total future time a system is under an unsatisfactory state. Loucks (1997) calculated it as the probability of a system recovering once it enters an unsatisfactory state. Yazdani et al., (2011) characterised resilience as a more complex combined metric of four infrastructural qualities of robustness, redundancy, resourcefulness and rapidity. Kjeldsen and Rosbjerg, (2004) calculated resilience in three alternative ways: the inverse of the mean value of the time the system spends in an unsatisfactory state, the maximum duration of an unsatisfactory state and the duration of the 90th fractile of observed unsatisfactory periods. They concluded that the maximum duration metric provided the most accurate and comprehensible estimation of performance. A direct maximum duration calculation was also the resilience metric of choice by Moy et al. (1986) who selected it to enable and simplify the quantification of resilience and its incorporation into a mathematical programming model. Kundzewicz and Kindler (1995) also argued that a resilience definition based on maximum value is better than one based on a mean value, as the presence of small insignificant events may lower the mean value and present an inaccurate picture of actual overall system performance.

Using resilience as a performance criterion has also been investigated within several other areas of human, social and ecological systems science, from natural resource investigations (Tompkins and Adger, 2004), to coral reef surveys (Hughes et al., 2003) and within adaptive policy making (Adger et al., 2007), with a detailed review of cross sector resilience measures conducted by Hosseini et al. (2016). It has generally been concluded that building resilience into systems is an effective way to cope with environmental change characterised by future surprises or unknowable risks.

Despite several investigations involving resilience criteria (see above), few to date have applied the metric to a complex real-world WRM adaptation case study under deep uncertainty to identify optimal adaptation strategies from a wide range of potential supply and demand intervention options. Nor has a comparative analysis been conducted with results from current UK engineering practice, utilising the more conventional reliability metric (frequency of temporary water restrictions).

2.5.8 Flexibility

Flexibility is defined by Smit et al. (2000) as the degree to which a system is pliable or compliant. For WRM adaptation planning this generally translates to the planning objectives of identifying strategies that are ‘pliable’ enough to be easily altered or updated in the future as uncertainties diminish. Techniques and tools such as Real Options Analysis (Copeland and Antikarov, 2001), Adaptation Tipping Points (Walker et al., 2013a) and Dynamic Adaptive Policy Pathways (Kwakkel et al., 2015), have been developed as cost-benefit valuation tools to evaluate the benefits of incorporating more flexibility in planning. This involves identifying and comparing strategies that have a greater capacity to ‘branch’ and be cost-effectively altered in the future as more information becomes available and incorporates concepts such as expanding (Yeo and Qiu, 2003; Majd and Pindyck, 1987), deferring (Mcdonald and Siegel, 1986), contracting (Trigeorgis and Mason, 1996) or even abandoning assets (Myers and Majd, 1990) at a predetermined cost before a predetermined point in time to allow for adaptive decision making.

2.5.9 Risk-based planning

There are many formal methods used to measure risk. Often the probability of a negative event is estimated by using the frequency of past similar events (Stamatis, 2014), which is then multiplied by the severity of those events in order to calculate a level of risk. Knight (1921) established the distinction between risk and uncertainty, whereby risk is deemed a measurable quantity and uncertainty is immeasurable and not possible to directly quantify. When uncertainties increase the risks of events become increasingly harder to quantify as past trends are expected to change thus making probabilities of events difficult to predict. However, risk-based planning can still be utilised within problems under uncertainty. For example, in WRM planning, projecting the likelihood of drought events occurring by analysing historic data may no longer be a suitable practice under rising future uncertainties, however by analysing multiple future scenarios of supply and demand and then calculating the frequency and severity of detrimental events that are recorded can then be used to project an estimate of future system risks. Numerous investigations utilising risk-based metrics for analysing adaptation strategy performance have been conducted (Borgomeo et al., 2014; Brown and Baroang, 2011; Hall et al., 2012b; Kasprzyk et al., 2012b; Turner et al., 2014a) and the UK water industry recently produced guidance which is starting to introduce the concept of risk more formally in the planning process (UKWIR, 2016b).

2.6 Approaches for WRM adaptation planning under deep uncertainty

The emerging climate change adaptation agenda has motivated the academic community to develop and investigate a range of decision making methods for dealing with "deep” uncertainties in water resources system planning. The hydrological community is beginning to acknowledge that an overhaul is required in long-term water planning and policy (Gober, 2013) and the water industry must now face up to the reality of deep uncertainty. The question is whether the various approaches can help solve the problems at hand and can turn theory into engineering practice.

Recent international WRM literature includes a wide array of contrasting approaches, such as: Robust Decision Making (Groves et al., 2015; Lempert and Collins, 2007; Matrosov et al., 2009; 2013), Info-Gap decision theory (Ben-Haim, 2006; Korteling et al., 2013; Woods et al., 2011), Decision Scaling (Brown et al., 2012; Brown, 2010; Ghile et al., 2014; Turner et al., 2014b) and Robust Optimisation (Giuliani et al., 2014; Kwakkel et al., 2015; Ray et al., 2013; Watkins and Mckinney, 1997). The majority of established DMMs are developed to evaluate the *robustness* of a system, strategy or decision, which is the term commonly used to described the degree to which a water supply system performs at a satisfactory level across a broad range of plausible future conditions (Groves et al., 2008).

Alternative approaches include methods that incorporate a *flexibility* analysis within the adaptive planning process (e.g. Real Options analysis (Jeuland and Whittington, 2014), Adaptation Tipping Points (Walker et al., 2013a), Dynamic Adaptive Policy Pathways (Kwakkel et al., 2015) or methods that concentrate on characterising the *risks* of a decision and develop risk-based metrics for water resources planning (Borgomeo et al., 2014; Brown and Baroang, 2011; Hall et al., 2012b; Kasprzyk et al., 2012b; Turner et al., 2014a). There are also scenario-based frameworks for discovering, ordering and mapping the uncertainties within modern WRM problems (Beh et al., 2015b; Kang and Lansey, 2013; 2014; Lempert et al., 2008; Nazemi et al., 2013; Singh et al., 2014; Weng et al., 2010) and a range of advanced methods for developing the scenarios to represent alternative plausible future conditions of a system as reviewed by Mahmoud et al. (2009).

A number of these approaches incorporate state-of-the-art optimisation algorithms, with the most popular typically being Genetic Algorithms, often termed Multi-Objective Evolutionary Algorithms (MOEAs) (Deb and Pratap, 2002; Hadka and Reed, 2013; Kasprzyk et al., 2012b; Kollat and Reed, 2006;

Paton et al., 2014b; Wang et al., 2014), which has led to combined processes that merge MOEAs, DMMs and specific visualisation tools, such as: Many-Objective Robust Decision Making (MORDM) (Herman et al., 2014), Many-Objective Visual Analytics (MOVA) (Fu et al., 2013) or Visually Interactive Decision-making and Design using Evolutionary multi-objective Optimisation (VIDEO) (Kollat and Reed, 2007).

Table 2.1 presents a diverse list of existing DMMs and other related decision tools/approaches. The table gives key details of each methodology, their general methodology type (see below) and identifies key references, either for the methodology descriptions or examples where the methods have been applied to WRM problems/case studies.

The methodologies are each indicated as one of the following types: a '*base decision making method*' indicating it is a complete framework or algorithm approach for decision making under uncertainty with a clear set of unique procedural steps; a '*decision making method evolution'* indicating it is an advancement on an existing base DMM; a '*decision making tool'* indicating it is a method/computational tool for analysing or ranking strategies/decisions or a '*classical decision rule*' indicating it is classical mathematical theory used to rank strategies/decisions.

An in-depth comparative study of all available methods is not practical given the length of this thesis and the number of approaches. In order to narrow the range of methods explored and compared five prominent but contrasting '*base DMMs'* are selected for further, more detailed, qualitative analysis (see Chapter 3). However, several of the *decision making tools* and *classical decision rules* are also discussed where appropriate.

The five base DMMs (Info-Gap decision theory; Robust Optimisation; Robust Decision Making; Decision Scaling and Multi-Criteria Decision Analysis) are selected for further investigation as they are the more complete framework approaches for decision making under uncertainty. The base DMMs underpin the DMM evolutions and can be combined with the DMM tools and the classical decision rules in various interchanging ways. Analysing the base DMMs allows a more clinical review of the primary aspects of decision making under deep uncertainty and how the features of the different base DMMs handle the various components of the decision process.

Table 2.1: Decision making methods and alternative approaches / tools for application to WRM adaptation problems under deep uncertainty

Decision Making Method (DMM) / Decision Tool	Key references	Key methodological details	DMM type	Selected for detailed qualitative DMM review
Robust Optimisation (RO)	(Ben-Tal and Nemirovski, 2000; Chung et al., 2009; Deb and Gupta, 2006; Hamarat et al., 2014; Kwakkel et al., 2015; Perelman et al., 2013; Ray et al., 2013; Watkins and McKinney, 1995; 1997)	This method involves the application of appropriate optimisation algorithms to solve problems in which a specific measure of robustness is sought against uncertainty.	Base decision making method	Yes
Robust Decision Making (RDM)	(Bryant and Lempert, 2010; Groves et al., 2015; Kim and Chung, 2014; Lempert and Collins, 2007; Lempert and Groves, 2010; Matrosov et al., 2013, 2009; Tingstad et al., 2014)	This is an analytic framework that helps identify potential robust strategies, characterise the vulnerabilities of such strategies, and then evaluate trade-offs among them.	Base decision making method	Yes
Info-Gap decision theory (IG)	(Ben-Haim, 2006; 2010; Hall et al., 2012a; Hine and Hall, 2010; Korteling et al., 2013; Matrosov et al., 2013; Woods et al., 2011)	This is non-probabilistic decision theory that seeks to optimise robustness to failure, calculated as the maximum radius of localised uncertainty that can be negotiated while maintaining specified performance requirements.	Base decision making method	Yes

Decision Making Method (DMM) / Decision Tool	Key references	Key methodological details	DMM type	Selected for detailed qualitative DMM review
Decision Scaling (DS)	(Brown et al., 2012; Brown, 2010; Ghile et al., 2014; Li et al., 2014; Moody and Brown, 2013; Poff et al., 2015; Steinschneider et al., 2015; Turner et al., 2014b)	This is a bottom-up analysis approach to decision making beginning with a vulnerability analysis of the system or decision. A decision analytic framework and sensitivity analysis is used to categorise key conditions that will influence planning. Future projections are then used to characterise the relative likelihood of conditions occurring. A strategy is then devised to minimise detected risks.	Base decision making method	Yes
Many-Objective Robust Decision Making (MORDM)	(Herman et al., 2014; Kasprzyk et al., 2013)	The MORDM framework builds on the RDM framework to identify potential vulnerabilities in a system blended with a many-objective search operation.	Decision making method evolution	No
Adaptation Tipping Points (ATP)	(Haasnoot et al., 2015; Kwadijk et al., 2010; Walker et al., 2013a)	ATPs are the physical boundary conditions where acceptable technical, environmental, societal or economic standards may be compromised. These tipping points are projected and then used to sequence an adaptive strategy.	Decision making tool	No
Dynamic Adaptive Policy Pathways (DAPP)	(Haasnoot et al., 2013; Kwakkel et al., 2015; Walker et al., 2013a)	This method provides an analytical approach for exploring and sequencing a set of possible actions based on alternative external developments over time and is an add-on and advancement to the ATP methodology.	Decision making tool / evolution	No

Decision Making Method (DMM) / Decision Tool	Key references	Key methodological details	DMM type	Selected for detailed qualitative DMM review
Multi-Criteria Decision Analysis (MCDA)	(Belton and Stewart, 2002; Dorini et al., 2011; Figueira et al., 2005; Hyde et al., 2004; 2005; Hyde and Maier, 2006; Kim and Chung, 2014; Liu et al., 2013; Weng et al., 2010)	Strategies are evaluated against a range of criteria and assigned scores according to each criterion performance to produce an overall aggregated score, or the criteria are weighted into one criterion or utility function.	Base decision making method	Yes
Real Options Analysis (ROA)	(Deng et al., 2013; Jeuland and Whittington, 2014; NERA, 2012; Trigeorgis and Mason, 1996; Woodward et al., 2014; Yeo and Qiu, 2003)	ROA is a mechanism for valuating flexibility by evaluating concepts such as expanding or deferring; allowing decision makers to make changes to a strategy as new information arises in the future.	Decision making tool	No
Many-Objective Visual Analytics (MOVA)	(Fu et al., 2013; Matrosov et al., 2015; Reed and Kollat, 2013; Woodruff et al., 2013)	This approach blends improved high-dimensional multi-objective optimisation with highly interactive visual decision support.	Decision making tool / evolution	No
Visually Interactive Decision-making and Design using Evolutionary multi-objective Optimisation (VIDEO)	(Kollat and Reed, 2007)	This method is a visualisation framework intended to provide an innovative exploration tool for examining high-order Pareto-optimal solution sets.	Decision making tool / evolution	No

Decision Making Method (DMM) / Decision Tool	**Key references**	**Key methodological details**	**DMM type**	**Selected for detailed qualitative DMM review**
Linear Programming (LP)	(Beh et al., 2014a; Ben-Tal and Nemirovski, 2000; Liu et al., 2011; Moy et al., 1986; Ray et al., 2012)	This is a method to achieve the best outcome (such as minimum cost of a strategy) in a mathematical model whose requirements are represented by linear relationships. To incorporating uncertain variables this requires pre-specifying a set of 'known' parameters.	Decision making tool	No
Minimax Regret (MR)	(Eldar et al., 2004; Giuliani and Castelletti, 2016; Kim and Chung, 2014; Li et al., 2009; Savage, 1951)	This method aims to minimise the worst-case regrets. Regrets are the losses created from selecting one strategy over another, under an isolated or set of future scenarios.	Classical decision rule	No
Wald's Maximin Theory (WMT)	(Giuliani and Castelletti, 2016; Ranger et al., 2010b; Wald, 1945)	In Maximin theory decisions/strategies are ranked on their worst-case outcomes within a bounded space.	Classical decision rule	No
The Laplace Principle (LAP)	(Giuliani and Castelletti, 2016; Keynes, 1921; Laplace, 1951)	LAP is a decision rule/philosophy which asserts that equal probabilities should be assigned to each future event/scenario, if there is an absence of positive ground or reasoning for providing unequal ones. This makes it a risk neutral equal likelihood approach to decision making where the best average performing solution is deemed most favourable.	Classical decision rule	No

2.7 Summary

This literature review highlights the need for continued evolution and innovation in the planning approaches for water resources management in the UK (and worldwide) to better prepare the industry for a future of rising uncertainties. The main uncertainties highlighted are the increasing levels of climate change leading to rapidly growing uncertainties in the behaviour and reliability of many regional sources of water supply, as well as increased urbanisation and rapidly growing regional populations leading to rising demand uncertainties. A number of modern decision making methods for handling “deep” uncertainties are discussed and the need for further comparative studies of the various methods and metrics is highlighted, including additional testing on complex real-world case studies. The review reveals the pertinent timing of this work for the water industry and derives numerous areas for further qualitative and quantitative research.

The following chapter (Chapter 3) has been structured as a qualitative review and comparative assessment of the most predominant base DMMs in recent literature, selected from this literature review (see Table 2.1), that exhibit a diverse range of varied underlying processes and principles. The five methods selected are: (i) Info-Gap decision theory; (ii) Robust Optimisation; (iii) Robust Decision Making; (iv) Decision Scaling and (v) Multi-Criteria Decision Analysis, which are examined to the following criteria: (1) the handling of planning objectives; (2) the handling of adaptation strategies; (3) scenario construction and the handling of uncertainties; (4) the selection mechanisms employed; (5) the computational requirements of the methods; and (6) the final output formats.

The aim of the review is to break-down and examine the differences between methodologies; act as a research aid to assist decision makers in selecting a problem appropriate DMM; and to isolate key criteria for further detailed quantitative analysis. The review highlights the knowledge gaps and comparative areas deemed of most research interest before linking them to the quantitative work carried out in Chapters 4-7.

Chapter 3. Qualitative Comparison of Existing DMMs for WRM Under Uncertainty

3.1 Introduction

This work qualitatively assesses a range of Decision Making Methodologies (DMMs) for the long-term Water Resources Management (WRM) planning problem of supply meeting demand under future climate change, population growth/migration, urbanisation and other uncertainties. Each DMM aims to, for a given long-term planning horizon, determine the best adaptation strategy (i.e. set of interventions scheduled across the planning horizon) that are required to upgrade an existing regional WRM system that will satisfy singular or multiple objectives of maximising some applicable performance criteria or planning objective (e.g. robustness/resilience) whilst minimising others (e.g. cost/pollution). This chapter has been structured as a comparative assessment of the most predominant base decision making methods (DMMs), identified based on a detailed literature review presented in Chapter 2, in order to: break-down and examine the differences between methodologies; act as a research aid to assist decision makers in selecting a problem appropriate DMM; and to identify key criteria for further quantitative assessment. Five established DMMs are reviewed to six assessment criteria selected to evaluate the various aspects considered most important to the WRM problem in question (see Chapter 2). Each methods specific implementation is detailed and discussed in relation to each criterion in order to derive knowledge gaps and areas for further quantitative analysis and comparison.

3.2 Decision making methods under review

A number of DMMs have been developed to incorporate a wide range of “deep” uncertainties in the planning process but still deliver a logical “best” strategy(ies) to ensure a sustainable future whilst adhering to the needs of multiple-objectives. Difficulties arise when attempting to compare a wide range of contrasting DMMs which are often considered non-mutually exclusive or not entirely independent of one another. For example, Robust Decision Making

(RDM) could be coupled with a form of multi/many-objective Robust Optimisation (RO) techniques (Herman et al., 2014) or with Real Options Analysis (ROA) decision tools (Jeuland and Whittington, 2014). The principle characteristics of each individual DMM can become diluted making it difficult to differentiate between them, hence this chapter seeks to break-down and discuss the various features of each in order to better facilitate appropriate DMM selection in tackling future WRM problems under uncertainty.

The following material gives a brief description of each method under review in the context of WRM adaptation planning. The DMMs selected are the base decision frameworks and algorithm approaches that appear most frequently in recent WRM literature as well as discussion on several classical decision rules and decision making tools to explore the full scope of decision theory under uncertainty. A number of state-of-the-art experimental methods, such as: stochastic risk-based approaches (Borgomeo et al., 2014; Hall et al., 2012b; Turner et al., 2014a), vulnerability mapping methodologies (Nazemi et al., 2013; Singh et al., 2014) and adaptive pathway methodologies (Haasnoot et al., 2013; Kwakkel et al., 2015) are currently being developed, however this section focuses on the more established frameworks/approaches.

3.2.1 (i) Info-Gap decision theory (IG)

Info-Gap (IG) decision theory is a non-probabilistic decision theory that seeks to optimise robustness to failure, or opportunity for windfall success, under deep (or “severe”) uncertainty (Ben-Haim, 2001). This addresses two contrasting consequences of uncertainty, the threat of failure and the possibility of unimagined success (Ben-Haim, 2006). IG favours robustness of *satisficing* in its approach to decision making. A strategy of *satisficing* robustness can be described as one that will satisfy the minimum performance requirements (performing adequately rather than optimally) over a wide range of potential scenarios even under future conditions that deviate from the best estimate (Ben-Haim, 2001; 2010). IG evaluates the robustness of an adaptation strategy as the maximum radius of localised uncertainty that can be negotiated while maintaining these specified performance requirements (Hipel and Ben-Haim, 1999). Figure 3.1 gives a diagrammatic representation of the unbounded assessment of Info-Gap from a “most likely” scenario ($\tilde{u}$), exploring two uncertain parameters (U1 and U2) in staged expansions (α), until an unacceptable level of system performance is reached (r_c), known as the critical reward level. Opportuneness is also displayed, calculated as the shortest distance of uncertainty traversed to reach a highly desirable outcome (r_w), known as the windfall reward level.

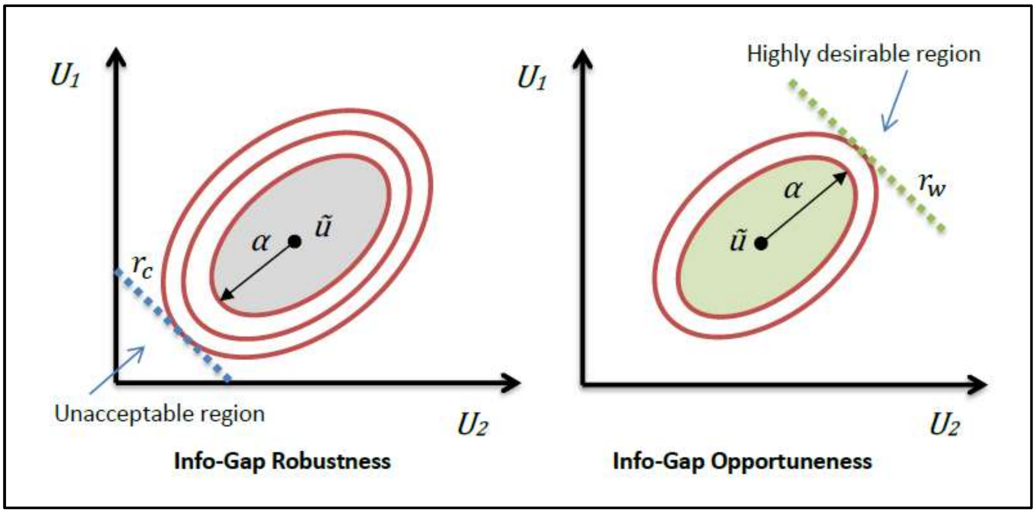

Figure 3.1: Info-gap robustness and opportuneness models

The IG analysis can thus visualise the robustness and opportuneness of different actions or strategies as a function of the level of uncertainty (Ben-Haim, 2012; Walker et al., 2013a), allowing the decision maker to analyse the trade-off between both characteristics for alternative strategies.

Examples of the application of IG decision theory in the development of long-term water management strategies can be found in Hipel and Ben-Haim (1999), Woods et al. (2011), Korteling et al. (2013), Matrosov et al. (2013), in application to flood risk analysis in Hine and Hall, (2010) and in the development of robust climate policies in Hall et al. (2012a). IG was found to resolve a lot of the weaknesses in current WRM predictive target headroom approaches by analysing multiple plausible representations of the future and establishing a suitable robustness measure to uncertainty; however it was not clear how the local assessment method itself impacted on the differing solutions produced in regard to alternative methods, nor is it clear as to the impact attributed to the origin of the IG analysis.

3.2.2 (ii) Robust Optimisation (RO)

Robust Optimisation (RO) involves the application of appropriate optimisation algorithms to solve problems in which a specific measure of robustness is sought against uncertainty, combining aspects from the fields of robust control, robust statistics, machine learning and robust linear and convex optimisation (Ben-Tal et al., 2009). Optimisation can be defined as trying to find the best solution among a set of possible alternatives without violating certain constraints (Walker et al., 2013a). It is mostly employed to identify a single best estimate solution to a singular objective problem (Bai et al., 1997). However, when dealing with multiple-objectives and deep uncertainties this predictive approach cannot be used, since often a theoretically “optimum” solution does not exist (Bankes, 2011; Rosenhead et al., 1972). RO can overcome this difficulty by finding the best solutions as a set of global Pareto-optimal robust solutions across the range of objectives (Coello, 1999; Deb and Gupta, 2006), leaving trade-offs among the various objectives out of the optimisation process and in the hands of the final decision maker (Kouvalis and Yu, 1997; Ben-Tal et al., 1998; 2000; Bertsimas and Sim, 2004). Detailed reviews of different aspects of optimisation within the WRM context have been conducted by Maier et al. (2014), Nicklow et al. (2010) and Reed et al. (2013).

A wide range of optimisation techniques are available for RO including, but not limited to: Genetic Algorithms (Deb and Pratap, 2002; Kollat and Reed, 2006), Particle Swarm Optimisation (Kennedy and Eberhart, 1995; Zarghami and Hajykazemian, 2013), Ant Colony Optimisation (Dorigo et al., 1996), Shuffled Frog Leaping Algorithms (Eusuff and Lansey, 2003) Generalised Reduced Gradient Algorithms (Frank and Wolfe, 1956), Linear Programing Techniques (Borgwardt, 1987) or combined process approaches such as Many-Objective Visual Analytics (Fu et al., 2013) or Many-Objective Robust Decision Making (MORDM) (Kasprzyk et al., 2013), which blend many-objective optimisation algorithms and visualisation tools with uncertainty analysis tools, such as those in RDM, to evaluate system sensitivities to uncertainties outside of those calibrated during traditional direct RO approaches.

Examples of the application of RO in the development of long-term water management strategies can be found in Kwakkel et al. (2015), Giuliani et al.

(2014), Herman et al. (2014), Kang and Lansey (2013) and Beh et al. (2015a) and for adaptive policymaking in Hamarat et al. (2013). Within this research it was found that RO could handle complex, deeply uncertain problems with large numbers of possible solutions. It was also able to derive candidate strategies of more precise sequencing over the planning horizon than more traditional approaches.

3.2.3 (iii) Robust Decision Making (RDM)

Robust Decision Making (RDM) is an analytic framework that helps identify potential robust strategies, characterise the vulnerabilities of such strategies, and then evaluate trade-offs among them (Lempert and Collins, 2007). The framework uses multiple scenarios of the future to identify the potential vulnerable sets of uncertain conditions for the candidate strategy(ies), known often as ‘scenario discovery’ (Bryant and Lempert, 2010; Groves and Lempert, 2007). This utilises data mining algorithms or ‘bump-hunting’ algorithms such as the patient rule induction method (PRIM) (Friedman and Fisher, 1999; Lempert et al., 2006) to locate boxes of key impacting regional data from high-dimensional data. Selected modifications are then made to the strategies to strengthen them against these detected vulnerabilities. It has been developed over the last 15 years, primarily by researchers associated with the RAND Corporation (Klitgaard and Light, 2005; RAND, 2013) and is used to identify a fixed plan that is robust (i.e. satisfices across a broad range of plausible futures, but may not necessarily perform optimally in any single future) (Lempert et al., 2003; Walker et al., 2013a).

RDM reverses the order of traditional decision analysis by conducting an iterative process based on a vulnerability-and-response-option rather than a predict-then-act decision framework, which is adaptation based on a single projected future (Groves and Lempert, 2007; Lempert et al., 2004; 2010). This is known as a bottom-up analysis and differs from the top-down method utilised by the majority of other DMMs (e.g. RO), as illustrated in Figure 3.2. RDM is often coupled with a regret-based or absolute-performance-based criteria (Lempert et al., 2006), in order to aid the strategy assessment process and isolate the most robust solutions. Although regret-based is often preferred as it focuses attention on the future scenarios that produce the most significant differences in alternative strategy performance.

Examples of the application of RDM in the development of long-term water management strategies can be found in Lempert and Groves (2010); Matrosov et al. (2013) and Tingstad et al. (2014). These evaluations found that RDM's bottom-up form of analysis, beginning with strategy formulation, was more recognisable to water managers, although the follow on concepts of deriving critically impacting scenarios was more conceptually challenging.

3.2.4 (iv) Decision-Scaling (DS)

Decision-scaling (DS) is another bottom-up analysis approach to decision making. It begins with a vulnerability analysis of the system or decision that is of interest to the planner rather than using an analysis of the future uncertainties as a starting point (Brown, 2010). This allows the decision maker to tailor or scale the range of uncertainties (climate projections) to focus on the critical (climate) conditions that may impact on the system. The approach uses a decision analytic framework and sensitivity analysis to categorise the key conditions that will influence planning, and then uses future projections to characterise the relative likelihood or plausibility of those conditions occurring. By using climate projections only in the final step of the analysis, the initial findings are not diluted by the uncertainties inherent in the projections (Brown et al., 2012; Stainforth et al., 2007). The result is a detected 'vulnerability domain' of key concerns that the planner or decision maker can utilise to isolate the key climate change projections to strengthen the respective system against, which differs from the bottom-up analysis featured in RDM, as illustrated in Figure 3.2.

New approaches are being sought to more accurately map the vulnerable conditions, such as modifications of PRIM and the Classification and Regression Tree (CART) method (Nazemi et al., 2013; Singh et al., 2014). This setup marks DS primarily as a risk assessment tool with limited features developed for overall risk management. Therefore a partnership of DS with algorithm approaches such as RO or Real Options Analysis (ROA) can improve follow-on identification of superior adaptation strategies.

Examples of the application of DS in the development of long-term water management strategies include: Brown and Baroang (2011), Brown et al. (2012), Moody and Brown (2013), Ghile et al. (2014) and Turner et al. (2014b). The evaluations of DS identified the benefit of tailoring climate variables and the estimate probabilities of the climate states to the system under review, removing the restricted dependency on uncertain climate projections and allowing greater vulnerability assessment and discernible direction for adaptation.

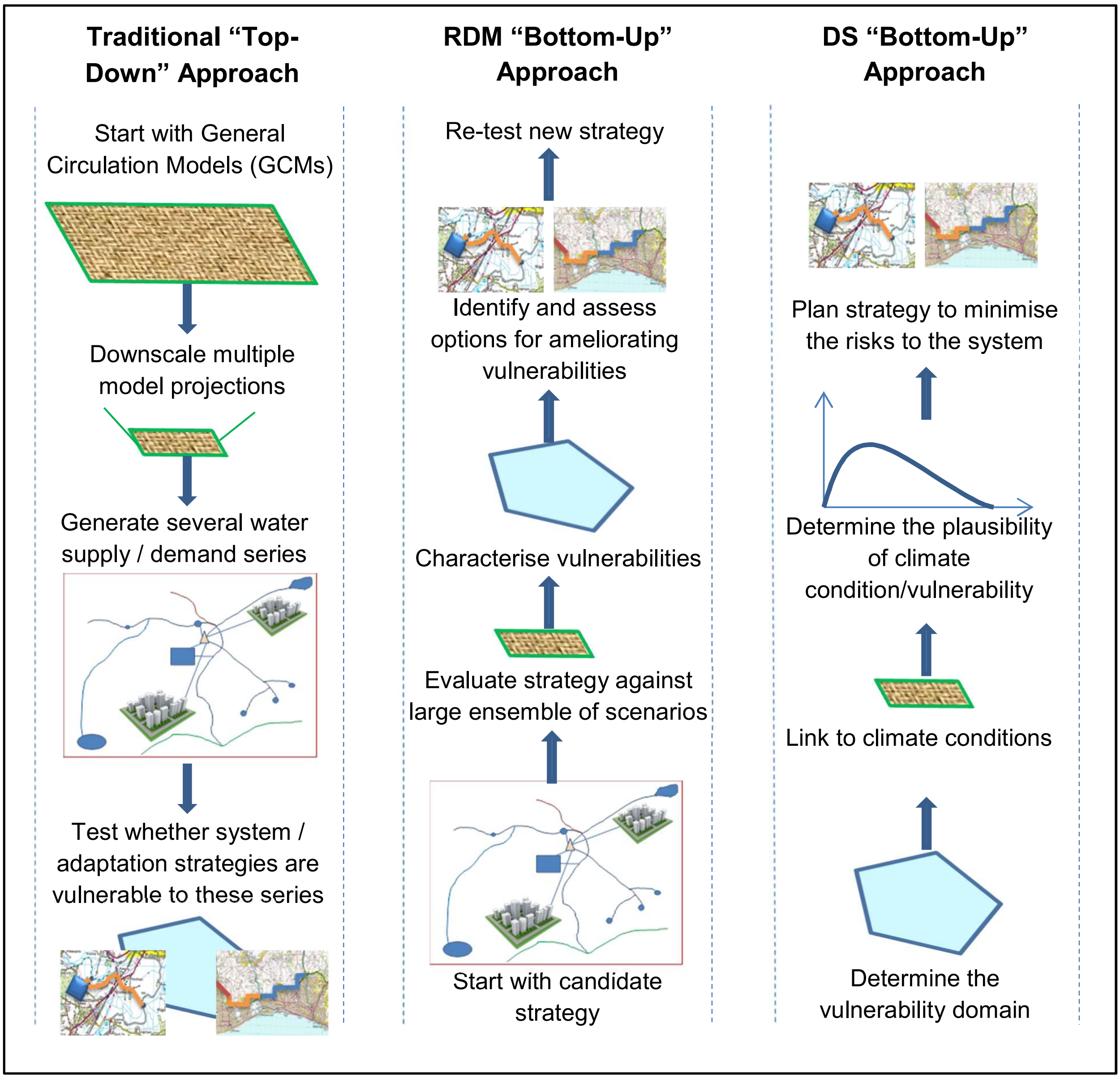

Figure 3.2: Traditional top-down decision approach vs DS and RDM bottom-up approaches – adapted from Brown et al. (2011), Hall et al. (2012a) and Lempert and Groves (2010)

3.2.5 (v) Multi-Criteria Decision Analysis (MCDA)

In Multi-Criteria Decision Analysis (MCDA) solutions are evaluated against a range of criteria and assigned scores according to each criterion performance to produce an overall aggregated score, or the criteria are weighted into one criterion or utility function. As this usually infers a deterministic approach, accounting for multi-objectives is regarded as more important than accounting for uncertainty (Ranger et al., 2010a). As such it is often performed as a preliminary step to isolate candidate individual resource options or to pre-select superior strategies to be further tested on DMMs more suited for “deep” uncertainty. If uncertainty is accounted for, it is usually done so by performing a sensitivity analysis on each criterion to uncertainty (Hyde and Maier, 2006; Hyde et al., 2005) or by placing joint probability distributions over all decision criteria (Dorini et al., 2010).

3.2.6 Other methods

A number of additional decision theories (or decision rules) exist which can either operate as individual DMMs themselves or act as rules/tools for more comprehensive decision frameworks; i.e. where decision rules can rank and compare options and identify the “optimum” decision outcomes, the DMMs describe the steps by which these decision rules are applied. Some of the more common decision rules are detailed below, including classical decision theories: Minimax Regret and Wald’s Maximin Theory; decision philosophy: The Laplace Principle of Insufficient Reason; and flexibility valuation tool: Real Options Analysis.

The Minimax Regret (MR) method aims to minimise the worst-case regrets. Regrets are the losses created from selecting one strategy over another, under an isolated future scenario (Savage, 1951; Eldar et al., 2004), and are derived from a ratio between the actual expected performance of implementing a strategy and the optimum performance projected out of all strategies tested (Loomes and Sugden, 1982). The optimum outcome under each future scenario is then subtracted from all other potential strategy outcomes producing an array of regrets or regret table (Ranger et al., 2010b). The maximum regret for each strategy is derived and those with the smallest maximum regrets are identified as the optimum strategies. Regret is the decision criterion most often utilised in

RDM and an example of the application of MR to water resources management can be found in Li et al. (2009) and in Kim and Chung (2014).

The Laplace Principle of Insufficient Reason (LAP) (Laplace, 1951) is a decision philosophy which asserts that if there is no known reason for predicting one of our subjects, rather than another of several alternatives, then relative to such knowledge each of these alternatives have an equal probability (Keynes, 1921). This theorises that equal probabilities should be assigned to each future scenario, if there is an absence of positive ground or reasoning for providing unequal ones (Sinn, 1980). Therefore, LAP is essentially a risk neutral equal likelihood approach to decision making where the best average performing solution is deemed most favourable.

In contrast to the risk neutral approach of LAP, Wald's Maximin Theory (WMT) (Wald, 1945) is well known to be extremely risk averse. WMT is a non-probabilistic theory where decisions are ranked on their worst-case outcomes within a bounded space (Ranger et al., 2010b). Hence, from a set of potential strategies, WMT identifies the best strategy as the one which provides the greatest expected performance from the worst projected scenario. Conversely, by playing it safe, the Maximin model tends to generate highly conservative decisions, whose price can be high. This is documented by Bertsimas and Sim (2004) as the *price* of robustness. Both the radius of stability model (Hinrichsen and Pritchard, 1986) and the Info-Gap robustness model (Ben-Haim, 2006) have been shown to be instances of the generic Maximin model (Sniedovich, 2010).

Real Options Analysis (ROA) includes concepts such as expanding (Yeo and Qiu, 2003; Majd and Pindyck, 1987), deferring (Mcdonald and Siegel, 1986), contracting (Trigeorgis and Mason, 1996) or even abandoning assets (Myers and Majd, 1990) at a predetermined cost before a predetermined point in time to allow for adaptive decision making and is a mechanism for valuating flexibility by allowing decision makers to make changes to a strategy as new information arises in the future (Copeland & Antikarov, 2001; Woodward et al., 2014). ROA can also utilise decision tree analysis to enable a branching evaluation of potential solutions (Dixit and Pindyck, 1994), and is becoming the most noted and recognised approach for evaluating the value of flexibility in decision making under uncertainty.

3.3 Selection of criteria for DMM evaluation and comparison

Despite several comparative investigations involving DMMs in application to WRM and climate change related problems (Hall et al., 2012a; Herman et al., 2015; Kwakkel et al., 2016; Matrosov et al., 2013; Ray and Brown, 2015; Walker et al., 2013a), few comparative examples involving practical application of DMMs to complex real-world WRM adaptation case studies exist to date, including examples of optimal adaptation strategy identification from a wide range of potential supply and demand intervention options. Nor has a break-down and comparison of the key criteria of the different methods been conducted in direct assessment of fundamental WRM issues.

In order to perform a more in-depth analysis of the various DMMs under review, each is evaluated in the context of WRM planning using a selection of criteria. Each criterion was selected because it is deemed to be among the most important or influencing factors that water resources planners consider when selecting an appropriate decision-making method for adaptive planning. Areas of interest for further comparative work are highlighted at the end of each section and a final tabulated summary of each method is given. The selected criteria are as follows:

- Criterion 1: Handling of planning objectives
- Criterion 2: Handling of adaptation strategies
- Criterion 3: Uncertainty handling
- Criterion 4: Selection mechanisms
- Criterion 5: Computational requirements
- Criterion 6: Output formats

3.4 Comparison of decision making methods

3.4.1 Criterion 1: Handling of planning objectives

The literature generally offers four discrete ways for dealing with deep uncertainty when making sustainable WRM adaptation strategies (van Drunen et al., 2009; Leusink and Zanting, 2009; Walker et al., 2013a; 2013b). These four fundamental planning objective types (and their most common definitions) are:

- *Robustness*: the degree to which a WRM system performs at a satisfactory level across a broad range of plausible future conditions or scenarios.
- *Resistance*: the performance of a WRM system under the worst projected future scenario or set of conditions.
- *Resilience*: the ability of a WRM system to respond to and recover (i.e. ‘bounce back’) from an undesirable/failure event.
- *Flexibility*: how easily a WRM system can be changed/adapted over time should external conditions change or more information become available.

The most common planning objective, or *design principle*, utilised across the DMMs is to maximise for *robustness* to uncertainty, which stands as the prime feature of IG, RO, RDM, and DS methods. Classical decision rules such as WMT and MR can be applied to design for maximum *resistance* (Walker et al., 2013a), while the ROA criterion is applicable to maximise system *flexibility*. MCDA has no set planning objectives for handling uncertainty, its main advantage comes in explicitly accounting for multiple objectives, which makes uncertainty analysis difficult to comprehensively examine in practice. If uncertainty is examined it is usually via a sensitivity analysis to quantify the impact of parametric variations on the individually weighted criteria. This is most closely related to a robustness analysis. For instance, Hyde and Maier (2006) developed a program to calculate the robustness of alternative solutions in MCDA via a distance-based sensitivity analysis of each criteria combined with a stochastic uncertainty analysis. Alternatively, several of the planning objectives listed above could be evaluated as separate criteria in the analysis and an average or aggregate score taken across the objectives. This interchangeability of criteria is a unique feature of MCDA methods, although it's uncertainty assessments are usually less comprehensive than other DMMs. Maximising *resilience* to uncertainty as a prime planning objective is generally an untapped resource in decision making under uncertainty within WRM literature and is more often recognised as a *performance metric/indicator* (along with reliability and vulnerability) as first recommended by Hashimoto et al. (1982). However, its recent attention in numerous high-level reports (Defra, 2016a; Environment Agency, 2015; Water UK, 2016) have qualified it for consideration as a primary planning objective in itself, as expressed in Walker et al. (2013a). As the frequency, severity and duration of future drought periods are an increasing uncertainty, designing a system that can securely manage and recover quickly from detrimental periods may be more beneficial than one that attempts to eliminate them entirely or reduce their occurrence. This reasoning is why *resilience* is being considered, not only as an advantageous performance metric, but also as a prime planning objective for improving a systems security to uncertain future events (van Drunen et al., 2009). Deriving an improved metric for *resilience* was also a noted conclusion in the Environment Agency (2013) report, which has only received a qualitative update to date (Environment Agency, 2015).

The planning objectives, although discrete in nature, can overlap in practical application. RO theory, although generally operationalised to maximise for system *robustness* (as the name *robust* optimisation implies) presents versatility in that in can be alternatively set up to optimise for substitute planning objectives. Establishing a firm definition of the primary planning objectives within a RO decision process is problematic due to the multiple ways the algorithms can be operationalised. The optimisation results are dependent on the setting of the *robustness* criteria, of which there is nothing preventing the application of any number of established decision theories; from an optimisation towards local *robustness* (e.g. IG), global *robustness* (e.g. RDM), the best worst-case outcomes (e.g. WMT), the least maximum regrets (e.g. MR) or even re-defining *robustness* as *flexibility* (e.g. ROA). *Robustness* itself is often defined differently throughout WRM literature, further confounding a firm classification of this design objective and there is, as of yet, no standardised paradigm for quantifying *robustness* in the water sector (Whateley et al., 2014).

Maximising *resistance* is a feature of the Maximin and Minimax family of metrics. However, it cannot be easily applied if dealing with an unbounded space of uncertainty, as there is no definitive worst-case scenario to be resistant against. In a bounded envelope of future uncertainty it would equate to a strategy that copes best across all (or against the worst) projected scenarios explored. This ultimately produces the most costly but least risk solutions. In order for IG theory to maximise for *resistance* it would need to first establish a desired region of the uncertainty to be robust against and then identify the most cost-effect strategy to meet this now designated highest level of localised *resistance*. This equates to the creation of a maximum *stability radius* and it is from this that the Maximin model and Info-Gap's theory of *robustness* are often related (Sniedovich, 2010).

Recent WRM literature is applying considerable attention to *flexibility* as a primary planning objective to handle deep uncertainties in adaptive planning. It is especially desirable to decision makers as it generally entails less commitment of capital expenditure early on in the planning horizon and presents the decision makers with a range of *robust* pathways to take in the future. This sacrifices a small quantity of short term *robustness* for greater long term cost-effectiveness. ROA is a popular decision criterion for assessing flexibility and has been combined with RDM for water resources planning by Jeuland and Whittington (2014). The decision-analytic framework they created identified a range of highly flexible strategies of varying strengths of short term *robustness* to long term *flexibility*, from which a decision maker can then derive an optimum trade-off. Lempert and Groves (2010) also used RDM to explore the potential positives of examining deferrable and expandable options within the strategies. Haasnoot et al. (2013) and Kwakkel et al. (2015) employed RO with multi-objective evolutionary algorithms to explored *flexible-adaptive* strategy designs (see section 3.4.2) known as 'dynamic adaptive policy pathways', which extend from 'adaptation tipping points' (Kwadijk et al., 2010; Kwakkel et al., 2015), to create an adaptation map showing the most promising adaptation pathways and then optimise the best ways to transfer from one pathway to another over time. Steinschneider and Brown (2012) also successfully combined ROA with seasonal hydraulic forecasts to create adaptation strategies with overall reduced system risks.

Real-life problems will generally entail a complex range of multiple objectives. As well as the previously outlined ‘primary’ planning objectives for handling deep uncertainties, additional design considerations/objectives for WRM adaptive planning will include a maximisation of cost-effectiveness, i.e. a minimisation of total capital and operational strategy costs over the planning horizon, as well as supplementary considerations such as minimising: resource usage, system energy requirements, energy costs, social objection and the environmental impact, to name a few. The DMMs analysed all have the capacity to be made multi-objective. The RO method can be implemented using multi-objective algorithms, although this is often limited to a small number of key objectives due to the increasing complexity of balancing optimisation search capability over a range of conflicting objectives. The IG, RDM, and DS methods can also be made multi-objective providing the objectives are weighted, or if the results are presented in multi-dimensional Pareto fronts (see section 3.4.6). Ranking type DMMs, such as MCDA, can handle the most objectives with the least difficulty and is the principal strength of this type of methodology, but this comes at a price of having to manually specify the limited number of adaptation strategies to be examined.

The DMMs that set weighted or constrained objectives first (e.g. MCDA, and some applied forms of IG and RO) often require specifying decision maker’s preferences before any analysis of strategies and future scenarios is carried out. In contrast, the bottom-up methods (RDM and DS), allow for objective preferences to be specified only when the full trade-offs between conflicting objectives have been identified, together with suitable strategies. Pre-processing objectives will reduce the range and diversity of final solutions derived, which places a much higher confidence in the decision makers preliminary judgments and reduces post processing control and flexibility.

From Criterion 1 it is identified that further work could be carried out to compare DMMs that focus on system robustness with those that emphasise system flexibility. The various potential definitions of system robustness should also be further explored as well as an examination into how resilience could be better incorporated into WRM adaptation planning.

3.4.2 Criterion 2: Handling of adaptation strategies

The definitions for strategic adaptations within WRM adaptive planning are as follows:

- *An Intervention Option:* a single water resource option (e.g. a new water resource asset or demand reduction measure) that could be implemented into a water companies future strategic plans.
- *An Adaptation Strategy:* a combination of intervention options sequenced over a planning horizon.

Adaptation Strategies can either be statically formulated or staged (Beh et al., 2014b; 2015a; Maier et al., 2016):

- *A Static Strategy:* options are selected but not time sequenced over the planning horizon.
- *A Staged Strategy:* options are selected and time sequenced over the planning horizon.

There are 3 further sub-divided definitions of *a staged strategy* formulation used in this evaluation (Lempert and Groves, 2010; Maier et al., 2016):

- *A Fixed Strategy:* pre-specified adaptation strategies are formed and assessed, and a final strategic design is established over the selected planning horizon as a fixed plan.
- *A Fixed-Adaptive Strategy:* the process of forming and assessing the strategies is an adaptive process; i.e. strategies are iteratively modified and updated based on vulnerability assessments or optimisation runs. The final selected strategy is however a fixed plan.
- *A Flexible-Adaptive Strategy:* defined as a strategy that can evolve or change as future conditions change. This strategy is devised with multiple future pathways to allow branching as more information becomes available and uncertainties diminish over time (i.e. the final selected strategy itself is a flexible plan).

DMMs that utilise *fixed* strategy formulations include IG and MCDA. Examples of *fixed-adaptive* strategy formulation include traditional applications of RDM and DS methods, which update their strategy components as system vulnerabilities and key scenarios are identified; or as in RO where optimisation algorithms, such as evolutionary algorithms, will modify individual intervention options within *fixed* strategies to "evolve" superior strategies from the original population. *Flexible-adaptive* strategy formulation involves a consideration of multiple-routes or "pathways" within the strategy designs. Application of ROA to an approach or the development of adaptive pathways are examples of *flexible-adaptive* strategy formulation because the strategies are designed to have added flexibility to the uncertain future conditions. This often involves a form of decision tree analysis in the strategy assessment process, whereby different strategy "branches" (i.e. variable pathways of new water resource options and their construction times over a planning horizon) are examined to identify strategies with greater potential to be altered at low cost in the future as more information becomes available (i.e. uncertainties diminish). These differ to fixed strategy designs which compare fixed sequences of new water resource options against one another to derive an optimal long-term sequence of intervention options based on the immediate data available. Fixed strategies lack this assessment of flexibility; however, flexible strategies also have their down side in that they can lead to reduced short term spending (and as such reduced short term robustness) to cater for the longer term flexibility.

DMMs can either assess *pre-specified* strategies or utilise *optimisation-generated* strategies to select strategies from a pool of available individual intervention options. The Enumeration method could also be applied to exhaustively test every feasible strategy combination; however, this is a computationally demanding task if a large range of individual intervention options are under consideration.

Examples of DMMs that typically utilise *pre-specified* strategies include IG, RDM, DS, and MCDA. Some of these DMMs will start with a full range of pre-specified strategies from which an optimum is selected (e.g. IG and MCDA), whereas methods RDM and DS will begin with individually pre-specified 'candidate' strategies which are then customised and developed during the assessment process in order to combat detected vulnerabilities. RO specifically utilises *optimisation-generated* strategies, automatically selecting and testing strategy combinations from a pool of intervention options. However, optimisation can also be combined with alternative DMMs to improve the range of strategies assessed. Examples of optimisation combined with RDM can be found in (Kasprzyk et al., 2012a) and in combination with DS and RDM in Hoang (2013) for water adaptation planning.

The number of *pre-specified* strategies for analysis is limited by computer processing speed/power. In current UK WRMPs (Bristol Water, 2014), *pre-specified* strategies are often reduced to small range of 'preferred' strategies following pre-selection by a form of MCDA or simplified optimisation process. However, thousands of strategies can theoretically be formulated and tested providing the efficiency of the water resources simulation models.

This computational efficiency is paramount when assessing *staged* adaptation strategies, as dynamic simulation models are required to evaluate the optimal staging/sequencing of options across the planning horizon (Beh et al., 2015a). This will be most impacting on methods that utilise optimisation (e.g. RO) because the frequency of simulation runs required will increase greatly as the time steps between potential construction windows is reduced. This will be less impacting on methods that utilise ranking based approaches, such as MCDA, or with DMMs that utilise pre-specified strategy generation; as although the range of potential individual adaptation strategies will increase, the number of assessed strategies can still be limited to a manageable volume. *Static* adaptation strategy generation can isolate the optimal collection of intervention options for immediate short term adaptation but does not offer any justifiable *optimality* or *satisficing* robustness (or flexibility etc.) to long term uncertainties. In short, adaptation analysis geared towards *static* strategies (i.e. that do not explore the sequencing of options over the planning horizon) makes little sense in a world of growing uncertainties.

*From Criterion 2 it is identified that further work could be carried out to assess the impact of utilising pre-specified vs optimisation-generated adaptation strategies as well as fixed vs fixed-adaptive vs flexible-adaptive adaptation strategy design*s.

3.4.3 Criterion 3: Uncertainty handling

The primary uncertainties in the WRM context are future projections of regional climate (i.e. water availability at all surface and ground water sources); demographics, i.e. the projections of future demand (influenced by uncertain rates of population growth, social adjustments and by climate change impacts); costs (both capital and operational) and changes in regulation (i.e. abstraction licenses). Uncertainties also exist in a number of other aspects including: the anticipated deployable output of new water sources; the security of new water sources (flooding uncertainty etc.); the anticipated effect of metering and other demand management incentives; the projected effect of leakage reduction plans; the time required to build (and have in operation) new large water asset schemes (such as large reservoirs and water reuse plants) and the rate of advancement in technology and information. The decision criteria ROA also has additional uncertainties in the representative long-term costing of flexibility. The handling of these uncertainties by each DMM is dependent on the format of the uncertainties that are presented.

The IG method represents uncertainty as a family of nested sets of plausible futures. This requires the future conditions or scenario projections (the uncertainties) to be ordered by some measure of increasing severity in order to identify a 'most likely' scenario/set of conditions to begin the analysis from. The nested ordering of scenarios allows the analysis to expand out in a proportional order of increasing uncertainty from the initial start point. Only the IG method requires a defined ordering of the future scenarios/conditions. The RDM method identifies the future scenarios/conditions that cause potential vulnerability to the initial candidate adaptation strategy selected. This form of 'scenario discovery' isolates only the key impacting range of projections, which are then utilised to modify the strategy into a more *robust* set-up. The DS method, rather than directly analyse scenario projections, conducts a more extensive vulnerability analysis over a wide range of condition variables to understand the sensitivity of the system to changing conditions. The plausibility of these conditions occurring is then estimated using recognised scientific projections. This reduces reliance on the demand and GCM-based climate projections, which potentially offer a constricted view of possible future states (Stainforth et al., 2007). RO is commonly used to perform a global examination of the entire range of bounded uncertainty, thus requiring no specific ordering, or prior 'discovery', of key scenarios. All DMMs can process large numbers of scenarios; however the greater the number of scenarios the longer the assessment run time. This will have particular impact on DMMs such as RO where non-linear optimisation problems, i.e. requiring evolutionary, combinatorial or stochastic algorithms to repeatedly sample the uncertainties will increasingly slow computer performance.

There are two commonly accepted approaches to planning and management when handling uncertainties. One is to assess the problem from the ‘top-down' and the other is from the ‘bottom-up’ (see Figure 3.2). Both assessment approaches can lead to an integrated plan and management policy (Loucks et al., 2005). RDM and DS are both examples of a ‘bottom-up’ approach (Dessai and Hulme, 2004; Lempert and Groves, 2010) also known as the grass-roots approach to scenario/strategy appraisal. This begins on the decision end with an assessment of system adaptive capacity and strategy vulnerabilities, which are then linked to potential climate conditions and demand projections (Smit and Wandel, 2006). The other DMMs are examples of the more traditional ‘top-down’ approach also known as the command and control approach (Loucks et al., 2005), which begins with climate scenarios and the supply and demand uncertainty envelopes, then strategies and adaptation policies are planned to alleviate the vulnerabilities exposed by these uncertainties (Wilby and Dessai, 2010). With IG the analysis still begins from the scenario end with the creation of an uncertainty model; however the envelopes of uncertainty are theoretically unbounded. This means the range of scenarios can expand and widen in parameters as the robustness analysis develops until established constraints are met. This combines aspects of the scenario led top-down approach with those of an expanding bottom-up vulnerability search area.

The ‘top-down’ approach presents an overwhelming level of uncertainty in climate and population projections, many of which may not be decision-relevant or are highly uncertain on the impact scale. Meanwhile, the ‘bottom-up’ approach presents a danger of under focusing on climate and population projections and utilising vulnerability spaces extrapolated primarily from experienced conditions and risks. Although recent applications seek to evaluate the range of climate conditions well beyond historical variability and known risks (Whateley et al., 2014). There exist very few frameworks that can comprehensively integrate risk analysis from both ends (Brown et al., 2012) and further quantitative examination of both concepts within a WRM framework would be beneficial to ascertain the benefits of both approaches for WRM adaptive planning. In general RDM and DS are much more 'hands on' approaches to decision making than the others as decision maker alterations can be made to adaptation strategies throughout the decision process.

From Criterion 3 it is identified that further work could be carried out to compare the contrasting effect of utilising a top-down vs bottom-up assessment structure and into the contrasting approaches for scenario creation / vulnerability mapping.

3.4.4 Criterion 4: Selection mechanisms

Definitions of key strategy selection mechanism terms (Ranger et al., 2010a; Hall et al., 2012a; Matrosov et al., 2013):

- *Satisficing*: an adequate level of service or system performance is established across a broad range of future scenarios.
- *Optimal:* the highest level of system performance or security is sought.
- *Local Robustness*: robustness to uncertainty is sought over a localised region of increasing uncertainty.
- *Global Robustness*: robustness to uncertainty is sought over the full range of discrete futures.
- *Regret*: the system performance lost from selecting one strategy over another under an isolated future scenario.
- *Worst-case*: the most impacting future scenario or set of conditions projected on a strategies performance.

Conventional water resources planning within the UK identifies strategies that can maintain a desired (i.e. target) level of service (or system risk). This is typically a cost minimisation-optimisation process whereby an *optimal* strategy is selected that best fits to the established target headroom projection. However, in the face of widening climate change and demographic uncertainties an *optimal* solution becomes unfeasible. This implies a general mechanism of *satisficing* required across all the DMMs when applied to modern water resources adaptation problems. For instance, a WRM decision maker does not aim for the strategy that provides the most water output obtainable to increase system security or the cheapest possible solution to a singular future; they aim for the strategy that meets their target objectives over the most future scenarios for the lowest cost/environmental impact. In other words, an *optimal* state may not exist when uncertainties are deemed “deep” and multiple futures and objectives are being adhered to. The only exception is within decision theories MR and WMT where it can be argued that seeking the most cost-effective strategy that meets the *worst-case* scenario projected or minimises the worst-case *regrets* is an *optimal* performance mechanism. However, the desired level of service the system is targeting (i.e. its performance under given metrics) will still merely be *satisficing* in this *worst-case* scenario and thus always *satisficing* in one or more objectives, whilst seeking the *optimal* in another.

The theory of *robust satisficing* appears the dominant mechanism across the DMMs being developed. However there exists several ways to layout and map the uncertainties in order to establish the robustness functions. This is often separated into the concept of *local* or *global robustness. Localised robustness* is most widely associated with IG decision theory. Criticism has however been placed on IG’s handling of deep uncertainty (Sniedovich, 2012) because the *localised robustness* analysis centers on an initial ‘most likely’ projection (which may be challenging to establish) and requires the ordering of future scenarios into nested sets around this initial ‘most likely’ projection. The former issue tends to be subjective and the latter issue can present difficulties when the arrays of potential supply and demand scenarios are not monotonically increasing. However, increasing uncertainty out from a localised point of higher likelihood allows IG to perform a theoretically unbounded staged assessment of the uncertainty region (Korteling et al., 2013), in relation to the bounded assessment of a global analysis, although the IG robustness analysis must still remain within the boundaries of realistic projections.

A *global robustness* examination, such as the mechanism traditionally utilised by RO and RDM theories, do not require the ordering of future scenarios and so uncertainties inherent in the ordering process can be diluted out. However, a *global robustness* evaluation requires testing of all potential scenarios which extends computation time in relation to the localised alternative which will stop assessing a strategy to future scenarios once surrounding states have caused the system to fail.

In recent literature, Matrosov et al. (2013) conducted a comparison of RDM and IG for water resources system planning. For the RDM analysis they used a *regret*-based form of MCDA to select the initial candidate strategy and to rank the subsequent strategy modifications and a fractional-error method over three uncertain system parameters to construct the IG model. This allowed all parameters to expand proportionately over the region of uncertainty, leading to a quicker run time for IG over RDM as fewer scenarios were sampled; however their IG method had the draw-back of ignoring un-proportional scenarios (i.e. times when both supply inflows and demands were low) and only 40 out of a potential 64000 scenario combinations were examined due to the way the fractional-error model incrementally sampled the uncertain space in a uniform pattern. They found both approaches sought to identify *robust satisficing* rather than *optimal* decisions and utilised *fixed pre-specified* adaptation strategies. However, each delivered slightly different final adaptation solutions due to the alternative forms of uncertainty assessment and selection mechanisms. The author's final recommendations were for the joint use of IG and RDM for the planning of water resources systems as each method helped clarify the results of the other. Hall et al. (2012a) also carried out a quantitative comparison of IG with RDM for climate policy. They identified many similarities, including the incorporated concepts of *robust satisficing* over multiple plausible representations of the future and the fact that both can provide decision support in the form of trade-off curves when multi objectives are assessed on quantified system models (see section 3.4.6). IG differentiated by considering potential gains and losses if a situation should turn out better or worse than expected; however the decision process is largely dictated by the robustness function in application to WRM problems, as the function for an opportune outcome is difficult to firmly establish. Further evaluations of varying robustness measures from different DMMs were also conducted by (Herman et al., 2015) who discovered each DMM ranked solutions to differing performance levels and recommended further investigation.

Selection mechanisms can also include consideration of the performance metrics/indicators utilised. These indicate the performance of a water system to a single future scenario or set of conditions and thus can theoretically be employed by any DMM to quantify performance. Selected performance metrics are either established as individual criterions or combined into an aggregated metric and are used to analyse a system to a given future scenario via parameters such as the frequency, magnitude or duration of detrimental events (i.e. reliability, vulnerability and resilience (see section 2.5.7)). These aspects are often combined in some form to calculate a level of projected future *risk* to the system as presented in many risk-based planning methods (Borgomeo et al., 2014; Ghile et al., 2014; Hall et al., 2012b; Kasprzyk et al., 2012b; Kjeldsen and Rosbjerg, 2004; Turner et al., 2014a) or can be assessed individually to provide more detailed performance information. The alteration of performance metric utilised and its effect on optimal adaptation strategy selection for WRM has been examined (Kjeldsen and Rosbjerg, 2004) but is a topic with room for further study on real-life complex case studies, especially with regard to its impact on a detailed engineering level, i.e. the effect on the optimal timing and scale of interventions scheduled across a planning horizon. When dealing with a vast range of uncertainties (future scenarios) and wide choice of potential adaptation strategies, the varying level of system performance can then either be analysed as an array (or table) of *regrets* from one strategy to another or in the comparative adherence to target levels of performance (i.e. *absolute-performance* based criteria).

From Criterion 4 it is identified that further work could be carried out to compare the impact on adaptation strategy selection based on the contrasting selection mechanisms, namely the local vs global forms of robustness analysis (e.g. IG vs RO), the effect of varying the governing decision rules (e.g. regret vs non-regret (absolute-performance) based assessment criteria) and in the choice of performance metrics/indicators on ultimate adaptation strategy selection (i.e. risk-based vs single criterion (reliability/resilience)based performance metrics).

3.4.5 Criterion 5: Computational requirements

Assessment of the computational requirements of the DMMs is a highly subjective issue as it depends on the simplicity of the problem, the computational skills of the user and the efficient set up of the approaches. However, impacting factors can be identified. Any DMM that involves a large number of simulations of plausible futures will be computationally demanding and will continue to increase in demand with the number of future scenarios examined. The methods that require full global mapping of the future scenarios (e.g. RO) are more time intensive then DMMs that isolate specific ‘critical’ scenarios (e.g. DS) or DMMs that operate within a localised failure radius (e.g. IG). The assessment of RDM and IG on water resources system planning conducted by Matrosov et al. (2013) found RDM to be the more computationally intensive approach than IG, due to the wider set of scenarios analysed during sampling.

Another factor impacting on efficiency will be the number of objectives assessed. Linear methods for deriving optima for singular objectives will always be significantly quicker to run than multi-objective evolutionary or combinatorial optimisation processes because of the nature of computational algorithms that require iterations. The number of iterations required for the optimisation runs (e.g. in RO) or when re-testing for new system vulnerabilities (e.g. in RDM), will also effect computational performance. Pre-processing to reduce the number of individual intervention options, or removing scenarios that indicate no impact on the base case water system models can greatly speed up the computational time for large scale water resources simulations and assessments (Southern Water, 2009; Bristol Water, 2014).

The testing of pre-specified strategies (e.g. as in IG and RDM) will be less intensive to run, in comparison to the time demands inherent with optimisation techniques, as a limit can easily be quantified when testing a pre-specified number of strategies. For RO the optimisation process can take a significant amount of time to reach the Pareto optimum results if the optimisation technique utilised requires a number of iterations, especially if a complex water system with a high number of individual intervention options is under assessment. However, in contrast this allows the optimisation process to take into account a greater number of strategy combinations including those that may have been over-looked when pre-processing and pre-selection of strategies is made within methods such as IG and RDM. Although optimisation approaches also run the risk of falling into local optima if unsuitable algorithms are utilised. Application of the Enumeration method to test all combinations of adaptation strategies would alleviate these issues, however; this would constitute the most computationally demanding, often prohibitively expensive method.

Overall there are three general tiers of computational requirements. The simplest tier includes the DMMs that are straightforward to evaluate and would not require complex frameworks (e.g. MCDA, direct application of the classical decision theories or linear optimisation techniques). The second tier includes the approaches that require a high level of uncertainty assessment and/or vulnerability analysis but utilise pre-specified strategy testing (e.g. traditional RDM, DS and IG). The highest tier involves the complex optimisation processes or approaches that are utilising optimisation based strategy generation (e.g. complex forms of RO and DMMs incorporating multi-objective optimisation) as they comprise the greatest number of iterations.

Each DMMs inputs can be modified (sampling of future scenarios, pre-processing of intervention options etc.) to reduce computational demands. In general the number of future scenarios tested will have less impact on time compared with the efficiency/complexity of the water resources simulation models and the set-up of the decision/optimisation algorithms selected. Therefore, the computational proficiency when setting up the methodologies and models is paramount, particularly given that future investments in the water sector in response to climate change may be significant, hence justifying extensive simulation studies to identify superior adaptation strategies (Borgomeo et al., 2014).

From Criterion 5 it is identified that the computational demands / requirements can be a largely subjective issue, dependent on the given problem and the set-up of each approach. Further comparison work could be carried out to assess the performance of approaches from different tiers of computational requirements (e.g. IG vs RO) or the effect of utilising the more intensive optimisation processes (e.g. evolutionary) vs the less intensive optimisation processes (e.g. linear programs).

3.4.6 Criterion 6: Output formats

The output results from DMMs utilising optimisation processes can produce results from singular optima to Pareto fronts of results across multiple objectives. The latter allows the final decision maker to examine full trade-offs between the objectives, which can be further aided by utilising state-of-the-art visualisation approaches such as; visual analytics (Fu et al., 2013) or visually interactive decision making (Kollat and Reed, 2007). These approaches can reduce large Pareto optimal design sets into smaller, more manageable subsets of interest and filter designs down by objective or subjective values (Maier et al., 2014). An issue with optimisation outputs is in knowing whether true Pareto convergence has actually occurred or if optimisation has been prematurely terminated before optimal solutions are revealed. If the preliminary optimisation set-up and the initial setting of objective functions are poorly calibrated then there is also a risk of falling into local optima (Deb and Gupta, 2006; Kollat and Reed, 2006; Maier et al., 2014). In contrast, the DMMs that test a pre-specified set of *fixed* adaptation strategies will produce outputs for all the strategies selected. From this data, Pareto strategies can be derived to examine trade-offs across multi-objectives or singular optima selected if objective preferences are weighted or combined (Rangaiah, 2009). However, the range of potential strategies is limited to the initial pre-specified selection. Methods that test *fixed-adaptive* strategies will start with a single (e.g. RDM) or range of adaptation strategies (e.g. RO) which are then iteratively modified or evolved into the final “best” output strategy(ies).

DMMs that utilise *flexible-adaptive* strategy formulations may produce outputs in the form of decision trees or adaptive pathways (Haasnoot et al., 2013; Jeuland and Whittington, 2014); hence, no clearly defined fixed strategies will be derived either as singular optima or as Pareto results. Instead a range of strategies are identified with a branching structure, indicating multiple routes for adaptation. All this, however, provides additional challenges when communicating the results to different stakeholders and in ultimate adaptation strategy selection.

The DMMs under comparison may initially assess just two or more primary objectives during the main decision process and then further evaluate additional objectives in a post-processing phase of assessment. This provides more selective tuning by decision makers once the strategy objectives deemed most pivotal have been optimised to. In traditional UK WRM planning the primary objective is to maintain a desired target headroom level over a time horizon for the lowest cost. Secondary objectives, such as environmental impacts and resource usage, are typically addressed during the pre-processing/MCDA of individual options or in post-processing trade-off comparisons of selected preferable strategies. This is often considered a more manageable approach when dealing with pre-specified strategies but is limited when optimisation processes eliminate dominated strategies that may have revealed promising trade-off gains when secondary objectives are examined. This issue can be alleviated by incorporating more objectives into the main optimisation process, although this creates multi-dimensional outputs which can be more difficult for decision makers to then decipher and filter down to a final decision.

DMMs that offer more manual modifications (*fixed-adaptive* strategies) during the decision process (e.g. RDM and DS) provide the decision maker with more control over the option filtering process. This allows the final strategy outputs to take shape as the process unfolds. DMMs utilising pre-specified fixed strategy testing (e.g. IG) place a higher level of confidence in this pre-selection of adaptation strategies, whereas DMMs utilising optimisation (e.g. RO) place a high level of confidence in the initial parameter setting to decide the resulting outputs of superior strategies. DMMs that examine multiple objectives must also consider the appropriate presentation of Pareto optimal results, as isolating superior trade-offs across multi-dimensions can become highly convoluted if numerous Pareto optimal sets are generated.

From Criterion 6 it is identified that largely all DMMs can be manipulated to output strategy results in the form of singular optima or as Pareto optimal sets to multi-objectives. The differences come in the way the outputs are developed and in the number of strategies/solutions considered. The presentation of outputs from the decision analysts to the decision makers is also an important aspect, especially when trying to decipher optimal trade-offs across multiple objectives/dimensions.

Table 3.1 presents the key summary points derived from this qualitative comparison of the different DMMs in respect to the listed assessment criteria. The table details the methodologies in terms of their more traditional features/criteria; however it should be noted that many of the methodologies can overlap in respect of their constituent processes. For instance, optimisation can be applied to most DMMs, although literature examples of WRM adaptation planning utilising, for example, IG have largely employed pre-specified strategies for analysis.

Table 3.1: Summary table – Comparison of Decision Making Methods (DMMs) for WRM adaptive planning

Decision Making Method (DMM)	Evaluation Criteria					
	1. Handling of Planning Objectives	**2. Handling of Adaptation Strategies**	**3. Uncertainty Handling**	**4. Selection Mechanisms**	**5. Computational Requirements**	**6. Output Formats**
Info-Gap decision theory (IG)	Robustness	Pre-specified or enumerative, fixed strategies	Top-down structure. Scenarios ordered into nested sets of severity. Analysed outward from most-likely scenario established	Local satisficing robustness / opportuneness adhering to a failure / success criterion	*medium* computational demands / requirements	All strategies assessed to derive a singular *best* strategy or Pareto sets for multi-objective problems
Robust Optimisation (RO)	Robustness	Optimisation search, fixed-adaptive Strategies	Top-down structure. No severity ordering of scenarios required. No likelihood assumptions	Global satisficing robustness, adhering to weighted or un-weighted objectives and constraints	*high* computational demands / requirements	Pareto sets from multi-objectives or singular optimum / pareto-front from aggregated objectives
Robust Decision Making (RDM)	Robustness	Pre-specified, fixed-adaptive Strategies. Begins with single candidate strategy	Bottom-up structure. Scenario discover used to identify key impacting scenarios / projections. No severity ordering of scenarios required	Global or local satisficing robustness to scenarios derived from vulnerability analysis, assessed using regret or absolute-performance based criteria	*medium* computational demands / requirements	Singular best strategy established or Trade-off summaries produced to compare the most robust strategies modified from initial candidate strategy
Decision Scaling (DS)	Robustness	Pre-specified, fixed-adaptive Strategies	Bottom-up structure. System vulnerability analysis performed using condition variables rather than climate / demand projections. Scientific projections used to establish condition likelihoods	Global satisficing robustness over established vulnerability domain	*medium* computational demands / requirements	Singular best strategy established or trade-off summary derived to compare the most robust strategies over the vulnerability domain
Multi-Criteria Decision Analysis (MCDA)	Interchangeable	Pre-specified, fixed strategies	Characterises sensitivity to uncertainty as a criteria in the analysis	Weighted aggregate score	*low* computational demands / requirements	All strategies are scored and the highest ranking selected for trade-off assessment
Real Options Analysis (ROA) *decision tool	Flexibility	Pre-specified, flexible-adaptive strategies	Top-down structure. Scenario tree modelling or adaptive pathways to route flexible solutions	Global satisficing robustness to short term performance goals whilst maximising long term system flexibility	*medium* computational demands / requirements	All strategy outcomes assessed allowing trade-off comparisons of superior flexible solutions

3.5 DMMs and criteria selected for further quantitative analysis

The comparison of methods conducted in section 3.4 has indicated a number of key criteria/techniques that would benefit from further quantitative assessment on real-world case studies. The review highlighted seven areas of key interest in particular that present contrasting theories of handling uncertainty in the WRM context which, at the same time, have had limited literature attention to date. The seven comparative/investigative areas are as follows:

(a) A local vs global measures of robustness,
(b) Pre-specified vs optimisation-generated adaptation strategies,
(c) Top-down vs bottom-up assessment structures,
(d) Fixed vs fixed-adaptive vs flexible-adaptive adaptation strategy designs,
(e) Regret vs non-regret based assessment criteria,
(f) Singular optimal results vs Pareto optimal sets and
(g) Risk-based vs reliability and resilience based performance metrics.

The term r*esilience* has also been highlighted as a potential alternative primary performance metric and/or planning objective for water resources adaptation planning, which, to date, has yet to be clearly defined in WRM literature. Deriving an improved metric for *resilience* is also a noted conclusion in the recent Environment Agency (2013) report identifying the metric as a prime candidate for further research and quantitiative assessment.

To perform an in-depth examination of all DMMs and explore all the investigative areas highlighted above would be highly ambitious and not feasible given the quantity of fine detail that each comparative area warrants. Therefore, following the qualitative review of methods shown here several methods and criteria were selected for further quantitative analysis.

More specifically, Robust Optimisation and Info-Gap decision theory methods have been selected for further quantitative testing on real-world case studies (Chapters 4 and 5) to primarily explore investigative areas (a) and (b) and subsequently areas (d), (f) and (g) listed above. These two methods are selected because they allow an examination of contrasting local vs global measures of robustness (a) as well as the effect of utilising pre-specified vs optimisation-generated adaptation strategies (b). They also allow a comparison of a fixed vs fixed-adaptive strategy design allowing partial evaluation of investigative area (d). Both methodologies evaluate fixed rather than flexible strategies in a top-down assessment structure, however this reinforces their selection for this detailed investigation as assessing too many contrasting concepts in one study can make it more difficult to isolate the main impacting features that influence the DMM outcomes. Two case-studies are carried out, one utilising a risk-based performance metric (Sussex North – section 5.3) and the latter employing an individual criterion (reliability) based performance metric (Bristol Water – section 5.4), to explore investigative area (f). The results are also compared with strategy solutions derived using current practice (deriving singular optimal solutions) to allow an examination of investigative area (g).

3.6 Summary

A total of five DMMs (Info-Gap; Robust Optimisation; Robust Decision Making; Decision-Scaling and Multi-Criteria Decision Analysis) and several classical decision rules and decision making tools (Real Options Analysis; Minimax Regret; Laplace principle and Wald's Maximin theory) were discussed and compared qualitatively using six assessment criteria (handling of planning objectives; handling of adaptation strategies; uncertainty handling; selection mechanisms; computational requirements and output formats).

The qualitative comparison of methods conducted here indicated a number of key criteria/processes that would benefit from further quantitative assessment on real-world case studies. The review highlighted seven investigative areas of particular interest: (a) a local vs global measures of robustness, (b) pre-specified vs optimisation-generated adaptation strategies, (c) top-down vs bottom-up assessment structures, (d) fixed vs fixed-adaptive vs flexible-adaptive adaptation strategy designs, (e) regret vs non-regret based assessment criteria, (f) singular optimal results vs Pareto optimal sets and (g) risk-based vs reliability and resilience based performance metrics. The term *resilience* was also highlighted as prime candidate metric/planning objective for further research and quantitiative assessment.

Following the review DMMs Robust Optimisation and Info-Gap decision theory were selected for further quantitative testing on real-world case studies to explore investigative areas (a), (b), (d), (f) and (g). This quantitative study is now presented in Chapters 4 and 5.

Chapter 4. Methodology for Quantitative Comparison of DMMs for WRM Under Uncertainty

4.1 Introduction

The methodology presented in this chapter as well as sections of the subsequent case studies (Chapter 5) have been published in the following Journals: Sussex North case study – Journal of Water Resources Planning and Management (Roach et al., 2016b); Bristol Water case study – Procedia Engineering (Roach et al., 2015a).

The following quantitative work evaluates two established decision making methods and analyses their performance and suitability within real-world WRM problems. The methods under assessment are Info-Gap decision theory (IG) and Robust Optimisation (RO). The methods have been selected primarily to investigate a contrasting local vs global method of assessing water system robustness to deep uncertainty but also to compare a robustness model approach (IG) with a robustness algorithm approach (RO), whereby the former selects and analyses a set of pre-specified "fixed" strategies and the latter uses optimisation algorithms to automatically generate and evaluate "fixed-adaptive" strategy designs (see section 3.5). The study also presents a novel area-based method for IG robustness modelling for use when handling discrete scenario projections (developed during this research study) and assesses the applicability of utilising the Future Flows climate change projections in scenario generation for water resource adaptation planning, utilising a novel rolling flow-factor methodology (see section 4.4.1).

The methods are then applied to two case studies (detailed in Chapter 5) modelling Southern Water's Sussex North water resources zone (section 5.3) and Bristol Water's water resources zone (section 5.4), both situated in the UK. An alternative performance metric/indicator is used within each case study, with the former employing a risk-based measure of system performance and the latter applying an individual criterion (reliability) measure of system performance. This allows a comparative assessment of utilising a risk-based performance metric against a performance metric more comparable with conventional WRM practice; in order to examine whether the metric type selected can impact on the DMM outputs.

First the general WRM problem is described followed by the concepts of robustness, adaptation strategies, costs and the two alternative performance metrics utilised in this methodology. A description of the dynamic water resources simulation model developed for this study is then given, including the methods for generating supply and demand scenarios, before detailing the specific operation of the two decision making methods under review. An overview of the quantitative real-world case study work carried out is then given prior to full case study details, results and analysis (Chapter 5).

4.2 WRM problem definition

The WRM problem is defined here as the long-term water resources planning problem of supply meeting future demand. The aim is to, for a given long-term planning horizon, determine the best adaptation strategy (i.e. set of interventions scheduled across the planning horizon) that are required to upgrade the existing regional WRM system that will satisfy the multiple objectives of maximising the robustness of future water supply whilst minimising the total cost of interventions required. Robustness of water supply (see section 2.5.6) is evaluated across a number of different, pre-defined supply and demand scenarios which are used to represent uncertain future climate change and population growth. The above problem is solved by using the two different decision making methods, each with its specific implementation, tested over two real-world case studies. The results obtained by using the different decision making methods are compared after all strategy solutions are re-evaluated using the definitions of robustness, costs, risk and reliability outlined below:

4.2.1 Robustness of water supply

Robustness is commonly described in WRM literature as the degree to which a water supply system performs at a satisfactory level across a broad range of plausible future conditions (Groves et al., 2008). Robustness of long-term water supply is defined here as the fraction (i.e. percentage) of future supply and demand scenarios that result in an acceptable system performance (Beh et al., 2015a; Paton et al., 2014a; 2014b), i.e. as follows:

$$Rob_x = \frac{A}{U} * 100 \tag{4.1}$$

where (x) = an adaptation strategy index; (A) = the number of scenarios in which the system maintains an acceptable level of performance (defined in accordance to the performance metric selected) and (U) = the total number of scenario combinations (of supply and demand) considered. For example, if 90 (S) out of 100 (U) scenarios are deemed to have been met acceptably then the robustness of adaptation strategy x is 0.9, i.e. 90%. The acceptable level of system performance is dependent on the performance metric/indicator selected and is defined, in case study 1 (section 5.3), as a risk of water deficit occurring (equation (4.2)) or, for case study 2 (section 5.4), as a level of system reliability (equation (4.3)) being below a pre-specified target level for the duration of the long-term planning horizon.

4.2.2 Performance metrics

4.2.2.1 Water deficits

In this study a 'water deficit' (or water deficit event) is defined as the point at which a water system requires a temporary water restriction to be put in place (e.g. a temporary use ban). The implications of extended water restrictions have potentially severe economic, societal, reputational and environmental impacts, particularly in large conurbation areas (Environment Agency, 2015). A study by Thames Water estimated that the monthly cost for London alone under restriction would be upward of £7 – 10 billion (Thames Water, 2012). An estimate by AECOM put the cost of 3 years of drought conditions occurring in England in the 2050s as costing up to £80 billion if current adaptation approaches are not advanced (AECOM, 2016).

The circumstances that entail a water deficit occurring are dependent on the system under study. For instance, in the case studies to follow (Chapter 5) a water deficit is counted if the stored water levels in the main system reservoirs fall below an unacceptable pre-specified (threshold) trigger level on a given time step (day or month). A water deficit may be allowed to occur occasionally, in order to manage the water supply system during periods of drought. However, an empty reservoir causing an unfulfilled water demand is deemed unacceptable and is defined as a complete system failure. Therefore the performance (and target level of performance) of a water system is defined and calculated as the risk of a water deficit occurring (case study 1) or alternatively by the relative frequency of water deficits recorded (case study 2), without the system ever reaching complete failure.

4.2.2.2 Risk of a water deficit and reliability of a water system supply

The risk of water deficit occurring for a given adaptation strategy system (*x)* to an individual discrete scenario combination of supply and demand (*u)* is defined as follows:

$$Risk_{xu} = \left(\frac{\sum_{t=1}^{T} f_t}{T}\right) \times \sum_{t=1}^{T} \Delta V_t \qquad \text{(for each } x \text{ and } u\text{) (4.2)}$$

where (f_t) = a value equal to 1 if a time step *t* (day or month) contains a water deficit event, otherwise equal to 0; (ΔV_t) = the volume of a water deficit recorded in time step *t* (ML); (*t*) = time step index and (*T*) = the total number of time steps in the planning horizon (assuming these are of constant length). The first term in equation (4.2) (in brackets) presents the likelihood of a water deficit and the reminder represents the impact of water deficits (assuming that actual impact is proportional to the volume of water not delivered which, obviously, represents a simplification of reality).

The reliability of a water system is defined as the probability of water supply fully meeting demand required over the planning horizon and is estimated here as the relative frequency of a water system not being in deficit (Kjeldsen and Rosbjerg, 2004):

$$Rel_{xu} = \left(1 - \frac{\sum_{t=1}^{T} f_t}{T}\right) * 100 \qquad \text{(for each } x \text{ and } u\text{) (4.3)}$$

The reliability of the water system must remain at or above a desired, pre-specified target level of system reliability (r_e) for the system to be deemed as performing acceptably under a given future scenario (of supply and demand). Similarly when utilising the risk metric, the risk of a water deficit must be maintained at or below a desired, pre-specified target level of system risk (r_c), i.e. the following constraints must be satisfied:

$$Risk_{xu} \leq r_c \tag{4.4}$$

$$Rel_{xu} \geq r_e \tag{4.5}$$

4.2.3 Adaptation strategies

Different adaptation strategies can be produced for a given water resource network by employing different combinations of various water resource options (intervention options) arranged over a long-term planning horizon. The total costs of strategies in the form of Present Values (PVs) are derived using equation (4.6).

$$PV_x = \sum_{y=1}^{Y} \left[\frac{C_y}{(1+r)^{i_y}} + \sum_{i=i_y}^{I} \frac{O_y}{(1+r)^{i}} \right] \tag{4.6}$$

where (y) = the intervention option index, (Y) = the total number of intervention options in the (adaptation) strategy, (C_y) = the estimated capital cost of intervention option y (£M), (O_y) = the estimated operating cost of intervention option y (£M/yr), (r) = the annual discount rate, (i) = the time step of the planning horizon (in years), (i_y) = the year in the planning horizon option y is implemented and (I) = the total number of years in the planning horizon.

This calculates the present value of an adaptation strategy as the total discounted capital and operation costs of all intervention options employed in the strategy, derived by summing each (one off) discounted capital cost and the accumulating yearly operational costs of an option from the point of each options implementation in the planning horizon (i_y).

In practice each intervention options will have varying build times, i.e. a new large reservoir may take several years longer to construct than a new minor resource option. However, to simplify the optimisation problem here all intervention options within a strategy are assumed built and in operation from their selected point of implementation in the planning horizon. For instance, if a new reservoir is sequenced in a strategies planning horizon after 10 years then the discounted capital cost of the reservoir is added to the total cost of the strategy at this 10 year point. The new water supply addition from the resource to the system, and its accumulative operational costs, will also begin from this point. This simplification is deemed acceptable given the focus of the study is on the decision making methods utilised rather than on generating a precise real-world optimal strategy.

4.3 Dynamic water resources simulation model

A dynamic water resources simulation model has been developed that can replicate, using a daily or monthly time step, the supply and demand balance of a regional water supply system over a pre-established time horizon. Different regional water resource networks can be input to the model, along with future scenarios (of supply and demand) and potential new adaptation strategies, analysing the performance of each future system combination via selected performance metrics (e.g. risk of water deficit results). The simulation model is written in the Python programming language (Python Software Foundation, 2013), and scenarios and strategies can either be input manually or selected automatically using an appropriate optimisation algorithm (see section 4.5). Figure 4.1 presents a simplified flowchart of the general operation and processes of the dynamic water resource simulation model developed for this study. It’s set-up within the Info-Gap robustness model and the Robust Optimisation framework is shown in section 4.5; in Figures 4.6 and 4.7 respectively.

The simulation model requires three main data inputs: a pool of potential new intervention options (i.e. new resource options / demand management methods that could be applied to a water system) from which to form combinations of new adaptation strategies; a range of plausible supply scenarios (i.e. potential future regional precipitation and river flow projections applicable to the performance of all existing water resources in the system) and a range of realistic demand scenarios to represent uncertain future population and demographic changes.

The adaptation strategy generation process, the method of mapping/analysing the generated scenarios of supply and demand and the format of the final model outputs will vary depending on the specific decision making method utilised and is fully described in section 4.5.

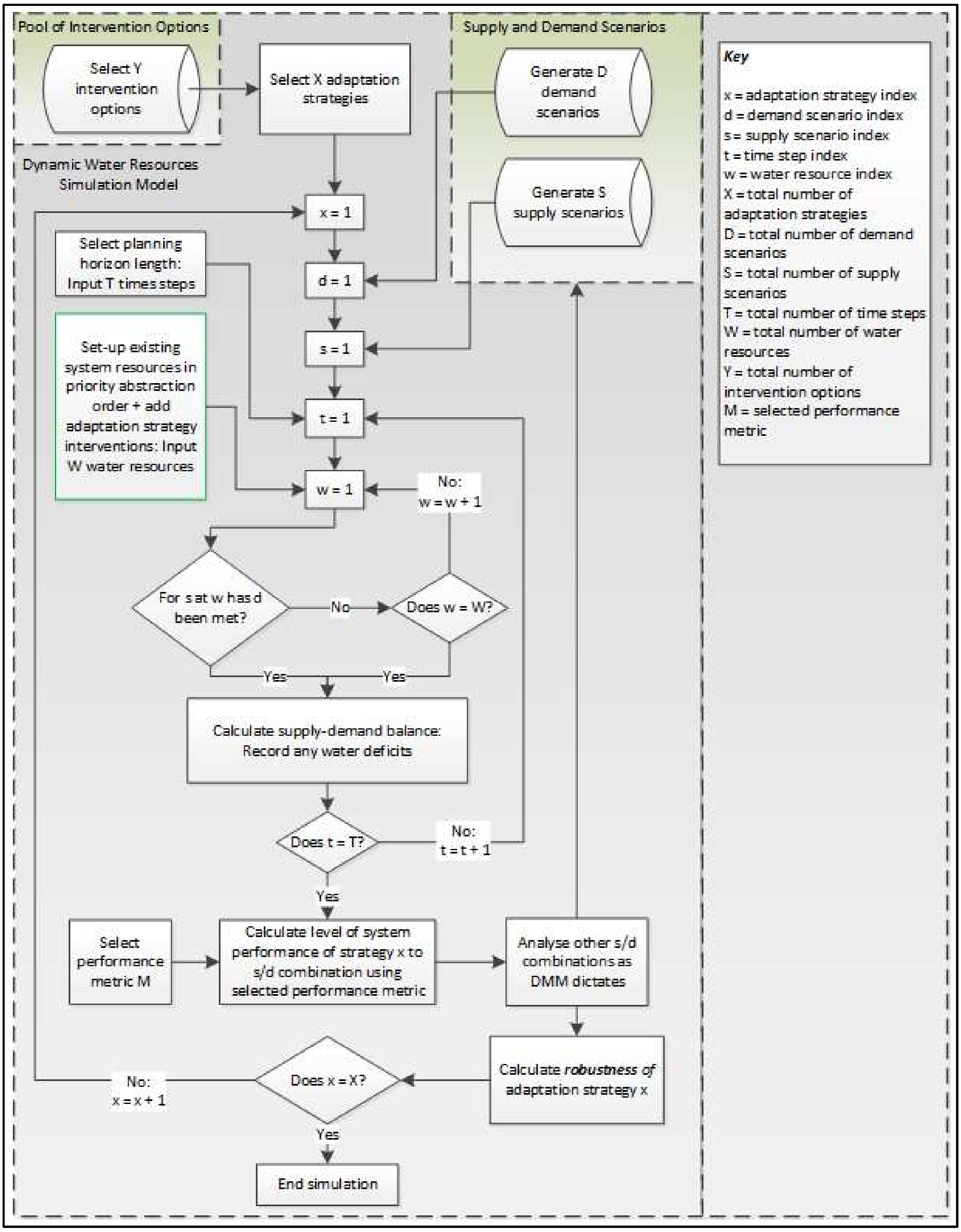

Figure 4.1: Simplified flowchart of the dynamic water resources simulation model developed

4.4 Regional supply and demand scenarios

When developing scenarios, the objective is to produce a small collection of vastly different but still highly plausible futures of a whole range of system factors (see section 2.5.5). For this study a wide range of plausible supply and demand scenarios deemed “equally likely” have been generated. Utilising likelihood assumptions will heavily weight, and thus generally favour, strategies that design to the “most likely” conditions, which cause the more unexpected future events to be ignored (a drawback of current engineering practice) and encourage the selection of a less “overall” robust system.

Effort has been made to represent the climate and population variability and extremes in future supply and demand in a thorough but plausible way by utilising the latest available projections. Resampling is also utilised for the supply scenarios to ensure a wide variation of potential futures are developed. Not ‘all’ potential scenarios are examined as this would be very computationally demanding; however, a suitably wide variation is utilised, including several ‘more severe’ scenarios, in order to sufficiently stress and assess the systems under study to future uncertainties.

The same methodology for generating supply and demand scenarios for a regional water resource zone has been utilised across both subsequent case studies and the follow on analysis work (Chapters 5-7). The methods and techniques for developing future scenarios is not one of the principle investigations of this research; however, an appropriate level of uncertainty must still be created and examined in order to produce credible outputs from the decision making methods. The process selected for generating scenarios is outlined below:

4.4.1 Generating supply scenarios

Following the literature review carried out in Chapter 2 a *prospective* (exploratory future trend) scenario type is selected for generating future supply scenarios for this study (see section 2.5.5). This form of scenario generation is based on the extrapolation and alteration of past data trends projected forward in time utilising plausible climate projections, combined with randomised variations in the timing and frequency of future drought periods, in order to produce a wide array of different scenarios that avoid directly copying historic patterns of events.

A reliable source of data for producing plausible scenarios of future hydrological time series and synthetic flows for a water resource zone in the UK is by using the UK climate projections (UKCP09) developed in 2009 by the UK Climate

Impacts Programme (UKCIP). The UKCP09 projections are still the leading source of climate information for the UK and its regions, but are scheduled to be upgraded in 2018 to the UKCP18 projections (Defra, 2016b). The projections are created to help users with the process of adapting their systems to a changing climate (UKCIP, 2009). UKCP09 only provides changes in climate and therefore requires hydrological modelling to derive hydrological time series that represent a range of climate model projections. However this has subsequently been addressed by the ‘Future Flows Climate Programme’ (Prudhomme et al., 2012) which uses the UKCP09 regional climate model to generate climate change projections of river flows. In this study the application of using the Future Flows climate/hydrology scenarios to generate future river flow projections for the region’s major contributing rivers and reservoirs is tested. The Future Flows project utilises the latest projections from the UK Climate Impact Program (UKCIP), derived from the UKCP09 regional climate models (RCMs) from the Met office Hadley Centre. They provide 11 plausible realisations (all assumed equally likely) of the river flows at various river gauging stations across England, Wales and Scotland and account for the impact of climate change to 2100 under a Medium emission scenario (Figure 4.3).

The key advantage of the Future Flow scenarios is that they are transient flow projections, so they do not require additional rainfall-runoff modelling and so can be directly utilised to continuously simulate the supply-demand balance over a given planning horizon. Direct use of UKCP09 projects is not suitable for this study as the projections provide “snap shots” of climate change for predefined time horizons and therefore cannot be easily manipulated for transient analysis. Using transient projections allows a direct analysis of the timing of interventions over the planning horizon.

The limitation of the current Future Flow projections is their utilisation of only a medium global emission scenario and their formation from the SRES emission scenarios (IPCC, 2000), scenarios recently superseded by the improved Representative Concentration Pathways (RCPs) (Moss et al., 2010), However, once resampled multiple times (as outlined below), the Future Flow projections provide an adequate range of uncertainty for this specific metric evaluation. Resampling of the flow projections (as outlined below) eliminates any bias in the selection of adaptation strategies due to the timing and duration of future drought conditions exhibited (which are fixed in time without resampling), and enables a sufficient investigation into the role of climate variability on the region's resources. The scenario generation process is not the focus of this study; however, it is recommended that water practitioners wishing to employ this methodology in practice should examine the widest range of plausible projections available.

In order to generate multiple future synthetic river flows and reservoir inflows for a region a Future Flows gauging site of closest proximity to the resource zone is selected. The specific time-series inflow/flow data required for each source of water, be it a reservoir or at a river abstraction point, is then translated using a monthly flow factoring method (Arnell and Reynard, 1996), which perturbs the historic flow data to match the flow changes projected at the gauging site. Flow factors describe the percentage change in monthly average flows over a 30 year historic period (1961-1990) with those of a 30 year future period at the gauging site (e.g. 2050s = 2041-2070). The limitation of a flow factor approach is that the historical sequencing of drought events is unchanged (Diaz-Nieto and Wilby, 2005), such that if a drought event occurs after 10 years historically it would appear in every climate change scenario after 10 years and force a similar pathway of adaptation strategies. In order to test the adaptation strategies against a range of different naturally varying scenarios, the historical flows are resampled (Ledbetter et al., 2012) using 3 month seasonal blocks (Dec-Feb, Mar-May, Jun-Aug and Sep-Nov) to create new realisations of historical climate. Each new flow projection is formed by resampling the past 100 years of flow records (1915-2014 inclusive), then selecting a 25 year period at random (Figure 4.2).

In order to then impose the transient climate change signal of the Future Flows scenarios within the resampled historical sequences a novel rolling flow factor method is devised to produce factors for each year in the future planning horizon. For example, to create flow factors for 2020 a future flow period from 2005-2034 is compared with the 1961-1990 baseline, for 2021 the future averaging period is advanced a single year to 2006-2035 and so on for each year in the planning/time horizon. The flow factors are then used to perturb the historic resampled river flow and reservoir inflow data at each source/site within the resource zone to ensure the system is modelling the same patterns of weather and climate change throughout the system at the same time (Figure 4.2).

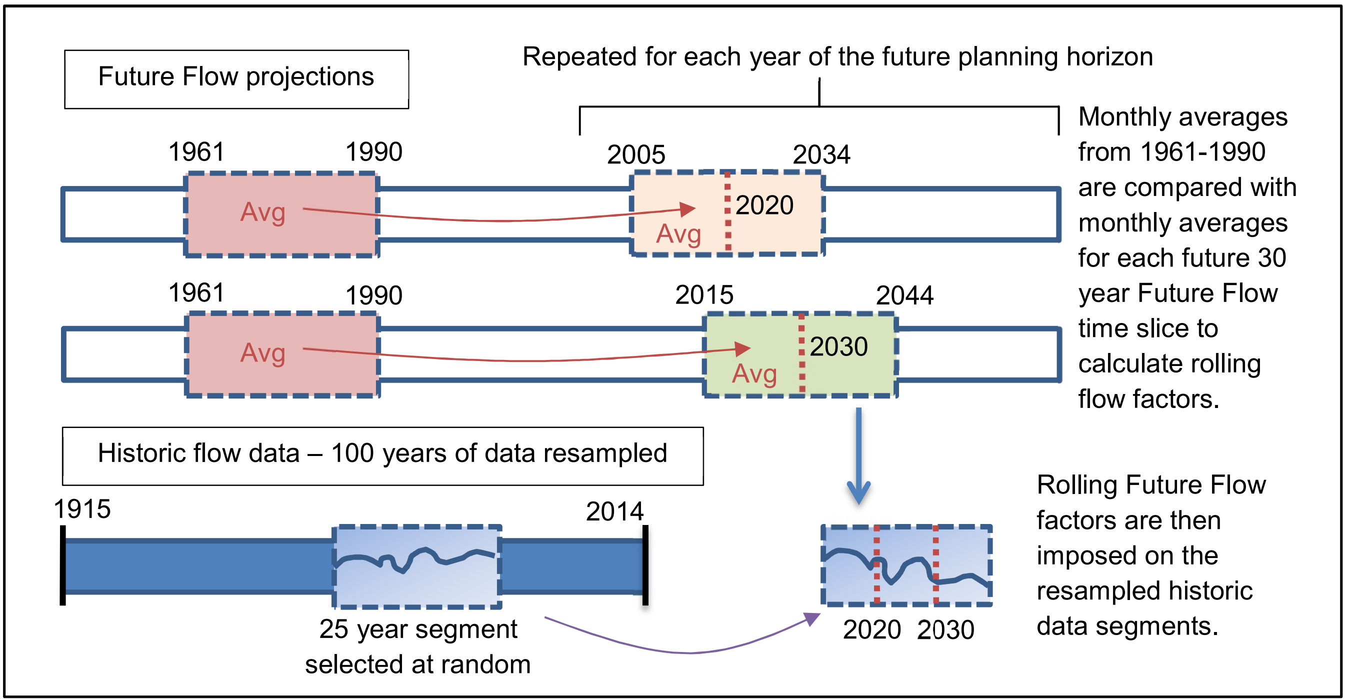

Figure 4.2: Supply scenario generation process – resampling and rolling flow factor method to generate transient flow projections imposed with Future Flow climate change signals

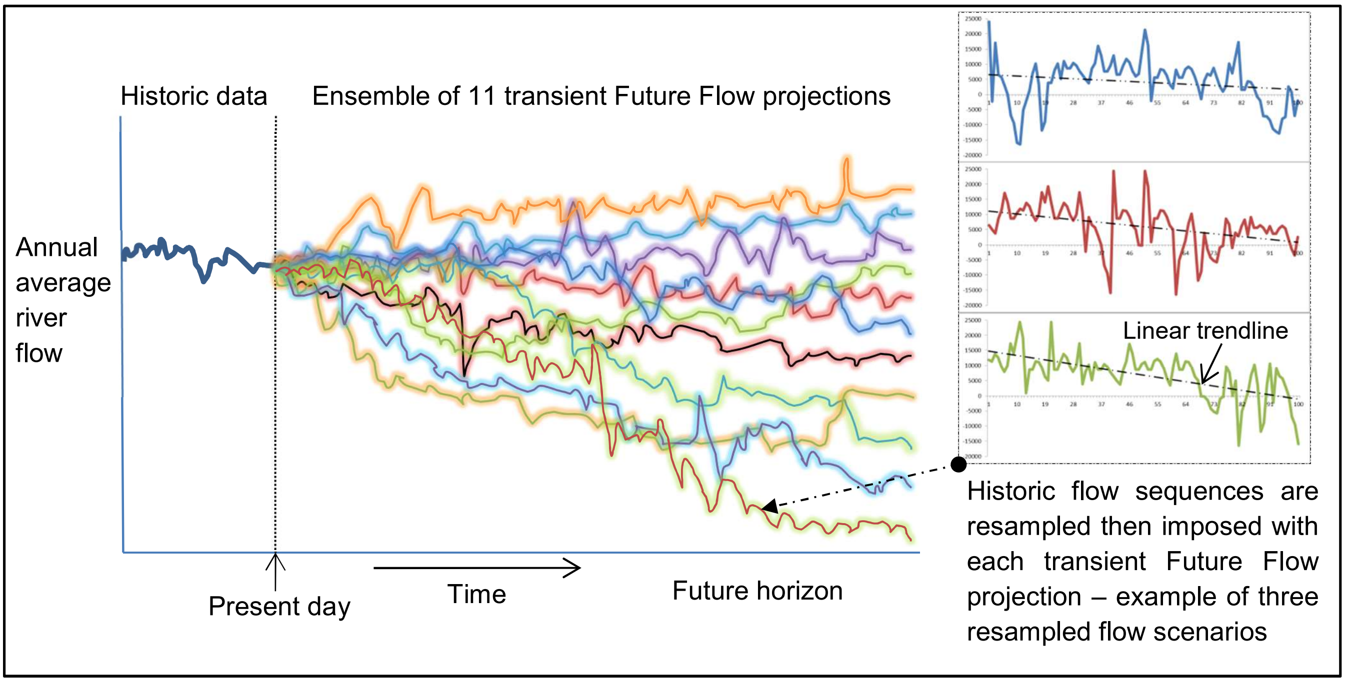

Figure 4.3: Future Flow climate/hydrology projections and example of three resampled flow sequences – conceptual drawing

Figure 4.3 gives a conceptual example of a historic river flow sequence and its 11 transient Future Flow projections. As detailed above, each flow scenario is formed by resampling the past 100 years of flow records (1915-2014 inclusive), then selecting a 25 year period at random before imposing each Future Flow transient climate change signal using the rolling flow factor method. Note in Figure 4.3 how the resampled flow scenarios maintain the downward trend of the given Future Flow projection but the stochastic resampling has re-ordered the drought periods to eliminate historic bias.

As the likelihoods of the different scenarios is not quantifiable the supply uncertainty is classified as “deep” (Walker et al., 2013b). The reliability of minor additional sources of water unique to the following case studies (Chapter 5), such as applicable minor groundwater sources or imported supplies from a neighbouring region, that are not projected to be significantly impacted upon by the regions climate change projections, will use their current daily/monthly contributing supply values as consistent inputs over the full planning horizon (Bristol Water, 2014; Southern Water, 2009).

Using transient sequences of flows is different to the standard engineering practice (the EBSD method) which assumes a single linear interpolation of supply availability from the baseline to the 2030s.

4.4.2 Generating demand scenarios

The method of demand scenario generation is specific to each case study and have either been developed using data tables from the latest regional WRMPs and supporting documentation (Sussex North case study) or by utilising WRMP data tables (per capita consumption etc.) combined with the Office for National Statistics (ONS) population projections (Bristol Water case study). Full demand scenario information for each case study is given in Chapter 5.

Demand scenarios for the Sussex North case study consist of 4 scenarios based on varying success levels following the enforced introduction of Universal Metering (UM) in the region. This requires full metering of all properties and non-household businesses by 2015 and the scenarios illustrate the projected effect of this introduction from a pessimistic demand increase to more optimistic results and also include scenarios of low leakage increases and high leakage increases following the implementation of the regional leakage program (Southern Water, 2009).

Demand Scenarios for the Bristol Water (BW) region consist of 3 scenarios of Low, Principal and High population growth used to perturb historic demand values, which are calculated subject to 3 alternative levels of demand uncertainty corresponding to the 80%, 90% and 100% target headroom calculations derived by BW (Bristol Water, 2014; UKWIR, 1998) resulting in 9 discrete demand scenarios.

Demand projections for both case study regions are derived from annual demand projections (or annual population growth / headroom projections in the case of the BW case study) that are typically listed in 5 year intervals. The 5-year demand data is interpolated to produce yearly average demands using linear interpolation between the known data values, which are then multiplied by monthly factors to reflect the changing seasonal demand averages employed by Southern Water (2009; 2014) and Bristol Water (2014), available from their WRMPs. These values are then used to create a range of discrete daily or monthly time step demand scenarios, either by perturbing the historic data with the projected population/headroom demand increases (as in the BW case study) or by directly interpolating the UM demand projections (as in the SW case study).

4.5 Decision making methods

4.5.1 Info-Gap decision theory (IG)

Info-Gap (IG) decision theory, as detailed in section 3.2.1, is a non-probabilistic decision theory that seeks to optimise robustness to failure over a localised area of deep (or "severe") uncertainty (Ben-Haim, 2001). IG evaluates the robustness of an adaptation strategy as the greatest level of localised uncertainty that can be negotiated while maintaining pre-specified performance requirements (Hipel and Ben-Haim, 1999). The Info-Gap robustness function, equation (4.7), expresses the robustness to uncertainty $(\hat{\alpha})$ of an adaptation strategy (x) as the <u>max</u>imum horizon of uncertainty (α) explored over a range of potential future scenarios of supply and demand $(u \in U)$, for which the <u>max</u>imum level of risk or reliability occurring (calculated using equation (4.2) or

(4.3)) maintains a target level of system performance (equations (4.4) and (4.5)), i.e. minimal system performance requirements are always satisfied (Ben-Haim, 2006):

$$\hat{\alpha}(x, r_c) = \max\left\{\alpha \colon \left(\max_{u \in U(\alpha,\tilde{u})} Risk(x,u)\right) \leq r_c\right\} \tag{4.7}$$

$$\hat{\alpha}(x, r_e) = \max\left\{\alpha \colon \left(\max_{u \in U(\alpha,\tilde{u})} Rel(x,u)\right) \geq r_e\right\} \tag{4.8}$$

where (*u*) = an individual discrete scenario combination (of supply and demand) and (*U*) = the total range (number) of scenario combinations considered. The Info-Gap robustness analysis begins from a "most likely" scenario combination (of supply and demand) ($\tilde{u}$) before expanding the analysis out over widening uncertain parameters (α).

A novel *area*-based method for IG robustness modelling of uncertain future supply and demand scenarios is presented in Figure 4.4. This method is introduced in order to directly utilise the discrete Future Flow scenario projections (Prudhomme et al., 2012) within the IG analysis, which traditionally uses continuous uncertainty variables. Each flow projection is highly variable, thus defining each horizon expansion as a function of increasing *distance* (α) cannot easily be established. The *area*-based method aims to solve this issue by first ordering the scenarios (both supply and demand) by their rank of severity (detailed below Figure 4.5) and then examining the various scenario combinations in an asymmetric search pattern (see Figure 4.4).

The method operates by first selecting and analysing a "most likely" scenario combination (of supply and demand) ($\tilde{u}$) on the system configuration (adaptation strategy) under assessment. If the given water system configuration performs acceptably (target levels of performance are satisfied) under this scenario combination then all adjacently ranked scenario combinations are then examined (see Figure 4.4 (a)). These scenario combinations are then analysed and the satisfactory/unsatisfactory performance of the system recorded. If a system fails (target levels of performance are not satisfied) under a given scenario combination then the search does not continue from this point in the uncertainty region, but may continue elsewhere if conditions are satisfied (see

Figure 4.4 (b)). The IG analysis then expands out over all adjacently ranked scenarios (the next higher and lower ranked scenarios of supply and demand) in an asymmetric search pattern, until no more immediate adjacent scenarios satisfy the selected performance requirements (or until all supply/demand scenarios meet constraints) (see Figure 4.4 (c)). The robustness level ($\hat{\alpha}$) of a strategy is then calculated as the sum of all satisfied scenario combinations (see Figure 4.4 (d)).

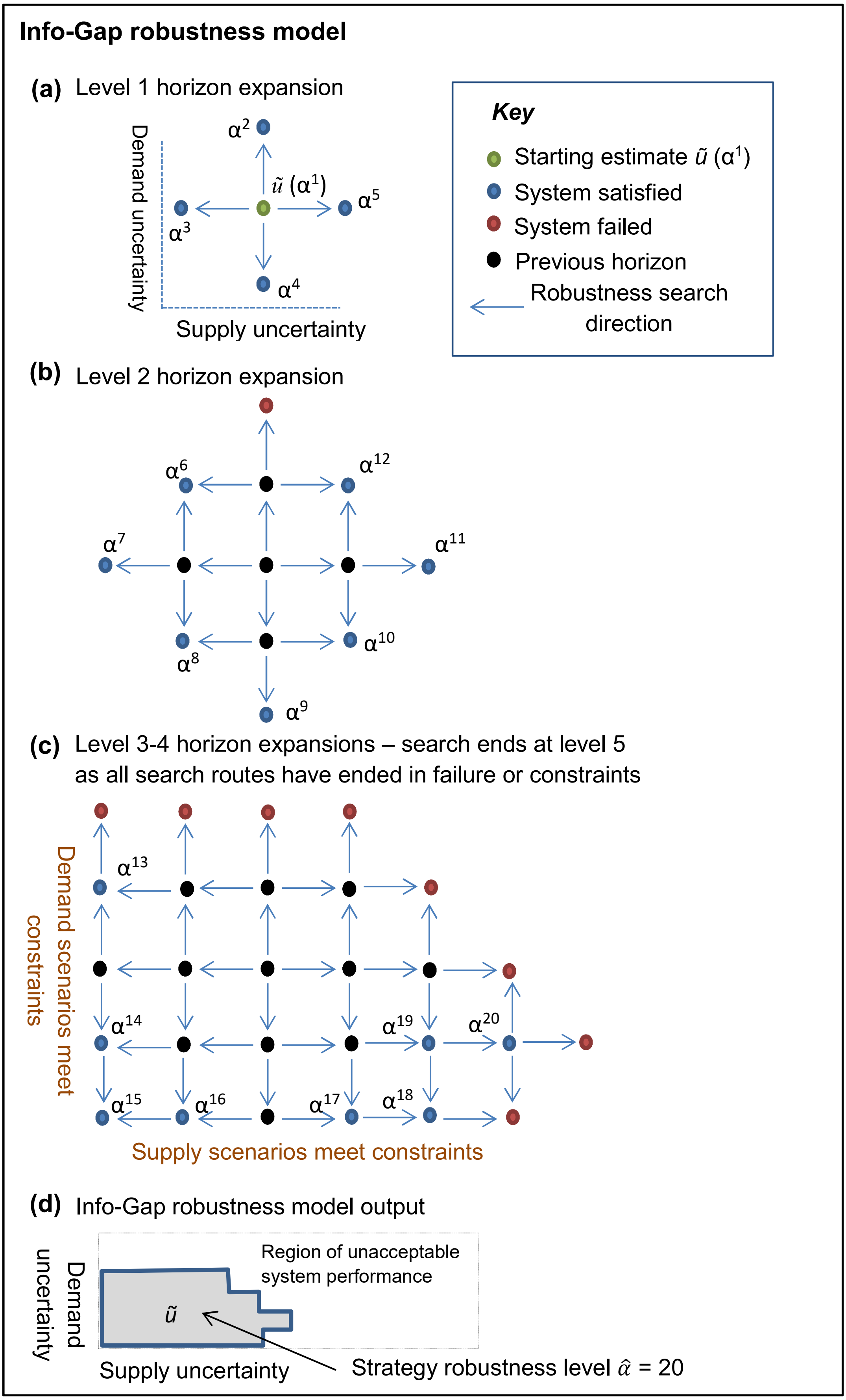

Figure 4.4: Info-Gap robustness model – utilising discrete scenario area-based robustness mapping to search the uncertainty region

The *area*-based methodology is designed to improve the IG robustness search process for handling uncertainties based on discrete scenario projections that are not monotonically increasing. Incrementally sampling uncertainties in proportional increases across all uncertain variables leads to a number of scenario combinations being ignored (Matrosov et al., 2013). The *area*-based method advances this by assessing all potential scenario combinations within each incrementally expanding robustness analysis. This robustness search technique allows more scenario combinations to be analysed and allows the robustness search to continue until all scenario expansion routes end in system failure. This calculates the expanding horizon of uncertainty (α) as a function of total *area* rather than as a function of maximum *distance* (Figure 4.5) and the IG robustness level is calculated as a sum of all successful (α') deviations (total no. of local scenarios (*u*) satisfied):

$$\hat{\alpha}(x, r_c) = \sum_{u=\tilde{u}}^{U} \alpha' \left\{ \alpha : \left(\max_{u \epsilon U(\alpha, \tilde{u})} Risk(x, u) \right) \leq r_c \right\} \tag{4.9}$$

$$\hat{\alpha}(x, r_c) = \sum_{u=\tilde{u}}^{U} \alpha' \left\{ \alpha : \left(\max_{u \epsilon U(\alpha, \tilde{u})} Rel(x, u) \right) \geq r_e \right\} \tag{4.10}$$

In order to later compare the IG results with those of the RO assessment the overall robustness to uncertainty is then calculated as a percentage over all futures scenarios considered using equation (4.1), where $(\hat{\alpha} = A)$.

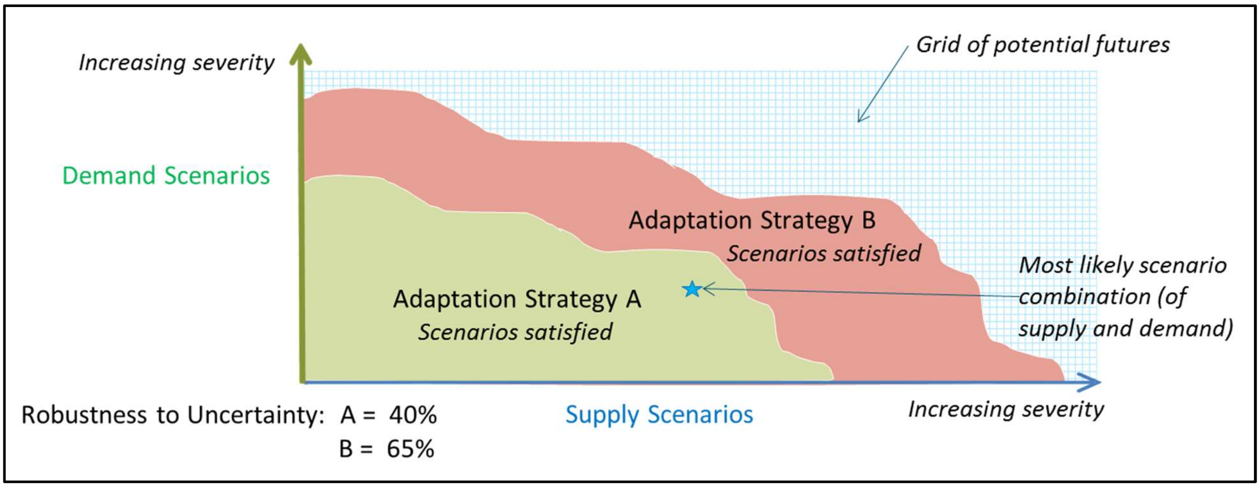

Figure 4.5: Example of two adaptation strategies tested using the Info-Gap area-based robustness model

The severity ranking of demand scenarios is straightforward as they are typically projected in a severity order. However the supply scenario ranking and ordering can be performed in a number of ways. For this methodology each supply scenario is tested on the baseline historical water supply system configuration, with the level of system risk or reliability calculated and used to assign relative severity ranks to the scenarios.

The selection of an appropriate starting point ($\tilde{u}$) within a theoretically unbounded region of uncertainty is a highly debated subject (Sniedovich, 2007; 2012). For both following case studies the median scenarios of supply and demand (following rankings as stated above) are selected for the primary IG runs (defined as U_{mid}). However, positions in the upper and lower quartile of scenario severity (defined as U_{high} and U_{low} respectively) are also tested in order to quantify the sensitivity of the ($\tilde{u}$) selection. The number of start points selected for examination is deemed appropriate given the complexity of the case studies and range of uncertainty examined. The range in supply and demand uncertainty is selected with great care and by considering a wide array of different data/information sources to produce a range of genuinely likely scenarios, as advised by Sniedovich (2007), detailed fully in Chapter 5 sections 5.3.2 and 5.4.2.

For IG, multiple adaptation strategies are manually prespecified from the range of potential option combinations and evaluated using the IG robustness model created. Either a subset of preferred strategies can be selected by the user or strategy combinations are generated either using complete enumeration (generate all possible combinations) or using random generation (generate a specified number of combinations at random). The specific method utilised for each case study is detailed in sections 5.3.2.5 and 5.4.2.5.

Figure 4.6 presents a flowchart of the IG methodology and its set-up / interaction with the dynamic water resources simulation model outlined in section 4.3.

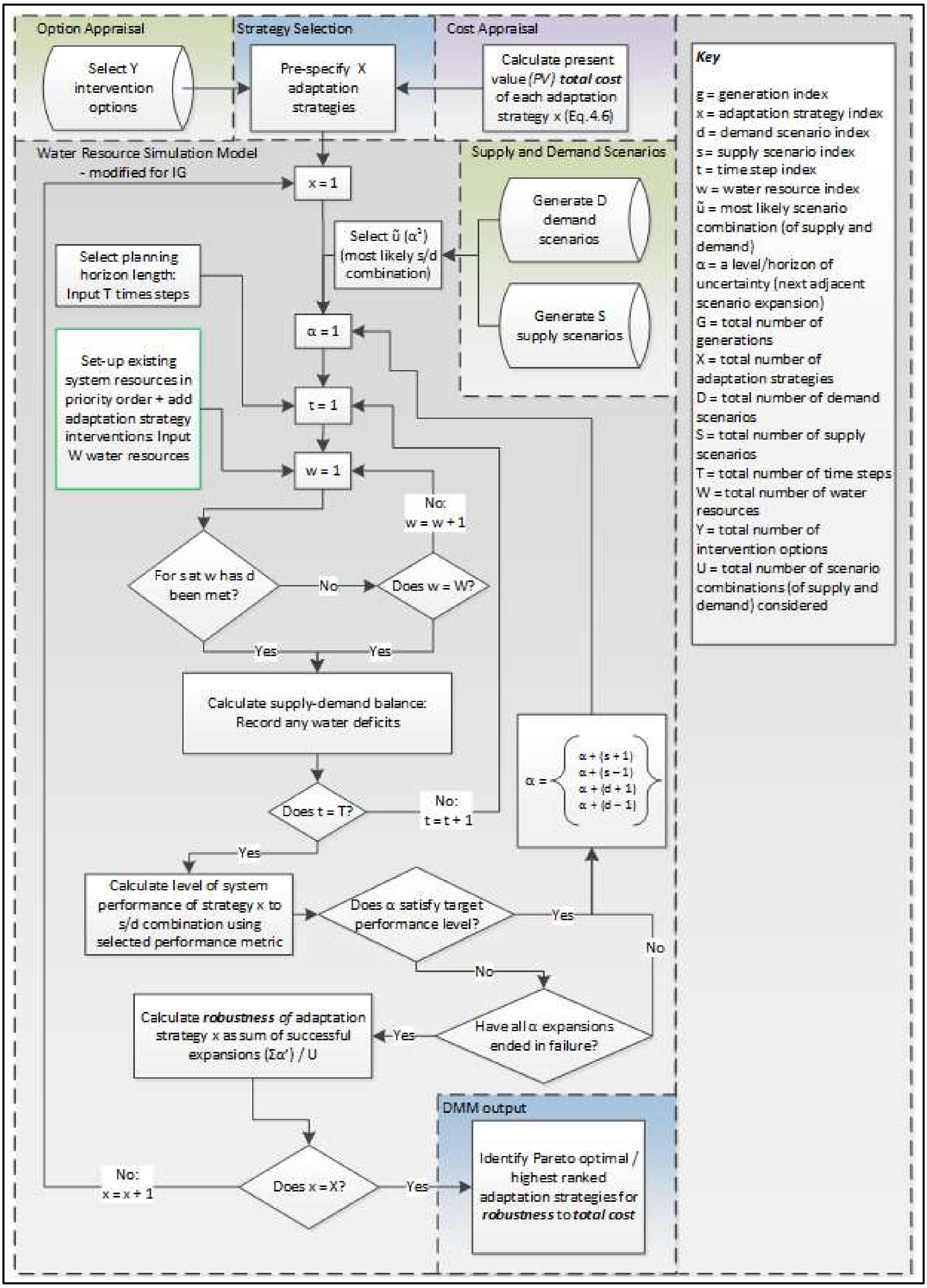

Figure 4.6: Flowchart of the dynamic water resources simulation model – IG methodology set-up

4.5.2 Robust Optimisation (RO)

Robust Optimisation (RO), as detailed in section 3.2.2, involves the application of appropriate optimisation algorithms to solve problems in which a specific measure of robustness is sought against uncertainty (Ben-Tal et al., 2009; see equation (4.1) for the defintion used here). For this WRM problem, the objective functions are the minimisation of cost (equation (4.6)) and maximisation of robustness (equation (4.1)). The optimising algorithm selected for this study is a modified version of the NSGA-II (Deb et al., 2000), as its high performance and capabilities in handling multi-objective water related optimisation problems is well documented (Kollat and Reed, 2006; Nicklow et al., 2010) and it is recognised as an industry standard algorithm (Wang et al., 2014). The algorithm uses integer values to select from the decision variables and is run using multi-processor parallel programming to increase run time efficiency.

The dynamic water resources supply and demand simulation model (see section 4.3) is combined with the NSGA-II optimisation algorithm, set-up using the R-programming language (R Core Team, 2013). The algorithm requires three main data inputs; a pool of potential new intervention options, from which to form combinations of new adaptation strategies, and the range of potential supply and demand scenarios (see section 4.4). The NSGA-II algorithm automatically forms a population of adaptation strategies, sequences the strategies across the planning horizon and then analyses their performance across all scenario combinations of supply and demand in the simulation model to the two objectives of cost and robustness. The decision variables are coded in a genetic code form such as [2, 10, 5, -1, -1, … n] where each chromosome is a different intervention option that could be included in an adaptation strategy (up to *n* number of variables(options)). The number of the variable indicates when in the planning horizon it is constructed (i.e. its point of adding additional water capacity to the system). For instance, the code example above is indicating five intervention options; the first three are implemented at 2, 10 and 5 years into the planning horizon, whereas -1 for options 4 and 5 indicate that they are not included in the strategy at all.

The best performing strategy codes are then carried forward, undergo crossover and mutation at random (based on selected probabilities) and then are re-analysed over several generations, with the aim of ultimately identifying the Pareto optimal set of results for robustness vs cost, where all non-dominated strategy results are discovered. The parameters used for each RO analysis are given in Chapter 5, sections 5.3.2.5 and 5.4.2.5, and further explanation of the NSGA-II operation can be found in Deb and Pratap (2002).

Figure 4.7 presents a flowchart of the RO methodology and its set-up / interaction with the dynamic water resources simulation model outlined in section 4.3.

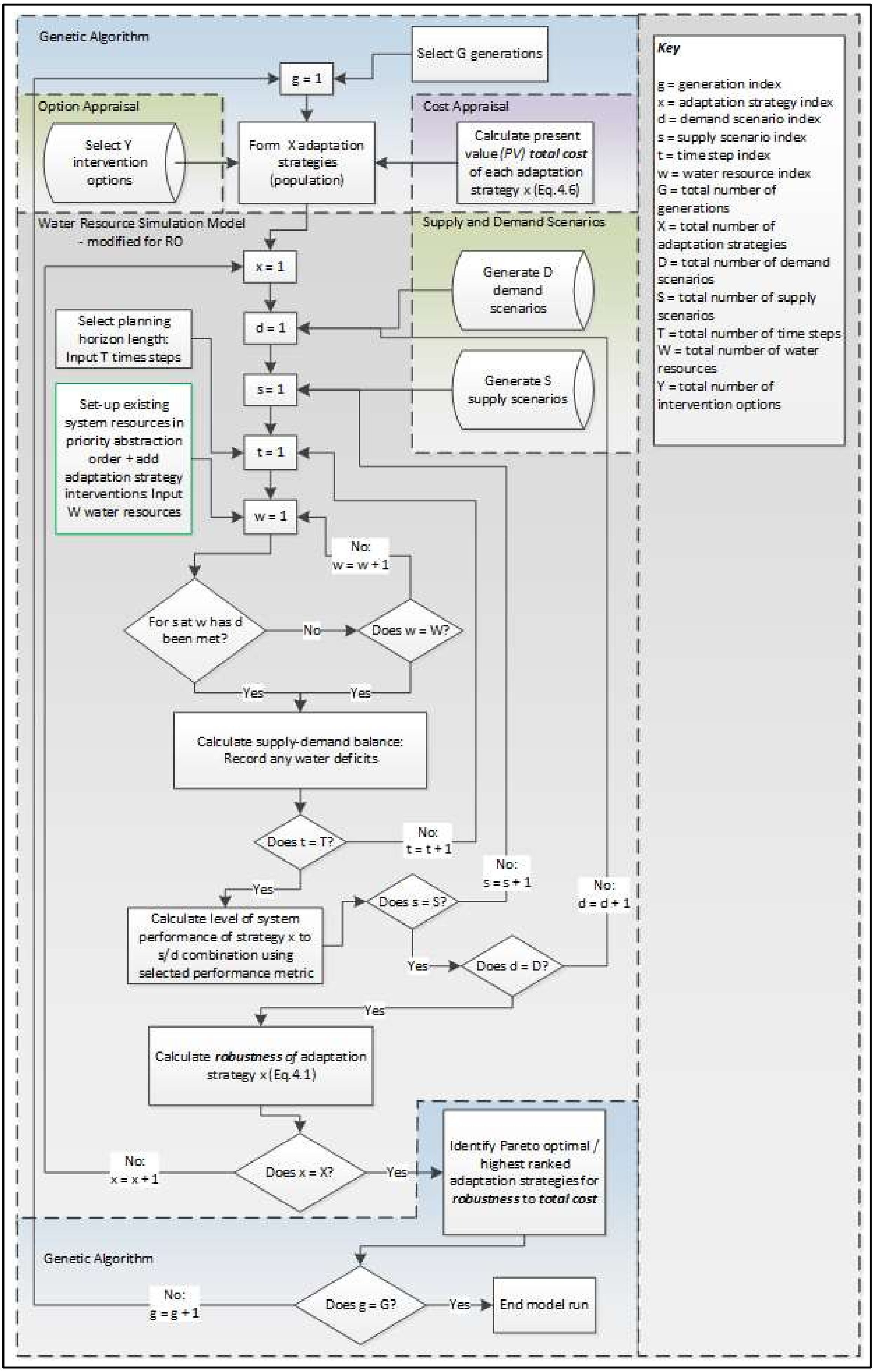

Figure 4.7: Flowchart of the dynamic water resources simulation model – RO methodology set-up

RO differs in its robustness analysis to IG in that it has been set up to assess the "global" robustness of a strategy rather than performing a "local" robustness examination prominent to IG decision theory (Figure 4.8). In a way it allows a "decentralised" robustness examination, testing a strategy's performance over all possible scenario combinations when calculating robustness, rather than isolating itself to a central "most likely" region, as implemented in the IG local "centralised", examination.

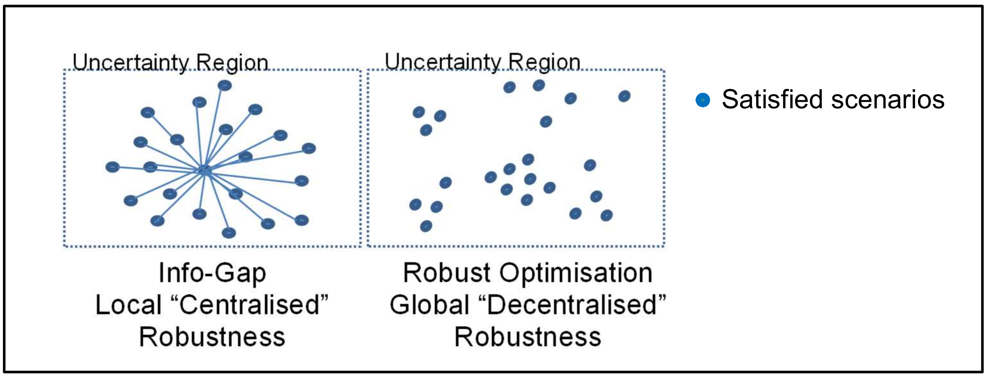

Figure 4.8: Info-Gap local robustness examination vs Robust Optimisation global robustness examination

4.6 Summary

This chapter outlines the general methodology for evaluation and comparison of two established decision making methods (Info-Gap decision theory and Robust Optimisation) on real-world water resource adaptation problems. A description of the dynamic water resources simulation model developed for this study is given, including the methods for generating supply and demand scenarios, before detailing the specific operation of the two decision making methods under review. A novel area-based method for IG robustness modelling for use when handling discrete scenario projections is presented as well as a novel rolling flow factor methodology for generating transient supply scenarios (developed during this research study).

The above DMMs are applied in Chapter 5 to two real-world case studies representing Southern Water's Sussex North water resources zone and Bristol Water's water resources zone.

Chapter 5. Evaluation and Comparison of DMMs for WRM on Case Studies

5.1 Introduction

Sections of the real-world case studies presented in this chapter have been published in the following Journals: Sussex North case study (section 5.3) – Journal of Water Resources Planning and Management (Roach et al., 2016b); and the Bristol Water case study (section 5.4) – Procedia Engineering (Roach et al., 2015a).

Following the qualitative review of methods carried out in Chapter 3, decision making methods “Robust Optimisation” and “Info-Gap decision theory” were selected for real-world case study evaluation and comparison. These two methods were selected because they allow an examination of contrasting local vs global measures of robustness (investigative area (a) from section 3.5) as well as the effect of utilising pre-specified vs optimisation-generated intervention strategies (investigative area (b)). They also allow a comparison of a fixed vs fixed-adaptive strategy design allowing partial evaluation of investigative area (d). Both methodologies evaluate fixed rather than flexible strategies in a top-down assessment structure, however this reinforces their selection for this detailed investigation as assessing too many contrasting concepts in one study can make it more difficult to isolate the main impacting features that influence the DMM outcomes.

Two case-studies are examined, the first utilising a risk-based performance indicator (equation (4.2); Sussex North – section 5.3) and the latter employing an individual criterion (reliability) based performance indicator (equation (4.3); Bristol Water – section 5.4), to begin to explore investigative area (g). The results are also compared with strategy solutions derived using current practice (deriving singular optimal solutions) to allow an examination of investigative area (f).

5.2 Case study explanation

The cases studies of Southern Water's Sussex North Resource Zone (section 5.3) as well as the more complex Bristol Water Resource Zone (section 5.4) are used here. The variations between the case studies and current engineering practice are shown in Table 5.1.

Table 5.1: Case study details and data

Case study / practice	**WRM Performance metric**	**Supply/demand uncertainty**			**Number of intervention options**	**Planning horizon (years)**	**DMM utilised**
		Demand scenarios (number)	Supply scenarios (number)	Total scenario combinations (number)			
Current UK engineering practice	Level of service – reliability metric	Variable – typically single median projection including headroom addition	Variable – typically single median projection	Variable – typically single supply-demand balance analysed	Variable – dependent of water resource network	25	Linear low-cost optimisation
Sussex North (section 5.3)	Risk-based performance metric	4	72	288	9	50	Info-gap and robust optimisation
Bristol Water (section 5.4)	Reliability performance metric – relative frequency	9	331	2,979	31	25 and 50	Info-gap and robust optimisation

The Bristol Water case study involves a more complex system and incorporates a wider range of uncertainty (a greater number of supply and demand scenarios) and a much greater number of potential intervention options. This allows an examination of how the two DMMs handle real-world WRM problems of varying complexity. An extended planning horizon (50 years) is applied in the Sussex North case study to incorporate more climate change and demand uncertainty over time than a typical 25-year planning horizon used by the UK water industry. A 25 year planning horizon is then applied in the primary Bristol Water investigation to allow a more direct comparison with the current UK practice, before a further comparative assessment utilising a 50 year planning horizon is carried out. An alternative performance metric is used within each case study, with Sussex North employing a risk-based measure of system performance and the Bristol Water applying an individual criterion (reliability) measure of system performance. This allows a comparative assessment of utilising a risk-based performance metric against a performance metric more comparable with conventional WRM practice; in order to examine whether the metric type selected can impact on the DMM outputs.

5.3 Sussex North case study

This section compares the contrasting mechanisms and outputs of two DMMs analysed (Info-Gap and Robust Optimisation) on a real-world WRM case study of the Sussex North Water Resource Zone in the UK. It also assesses the applicability of using the Future Flows climate change projections in supply scenario generation for water resource adaptation planning.

5.3.1 Case study description

IG and RO are applied to a case study of Southern Water's Sussex North Water Resource Zone (SNWRZ) shown in Figure 5.1, a region in the South East of England that was listed as a region under "a serious level of water stress" (Environment Agency, 2007; 2013b). The existing water resources for the SNWRZ system are shown in Figure 5.1 and listed in Table 5.2.

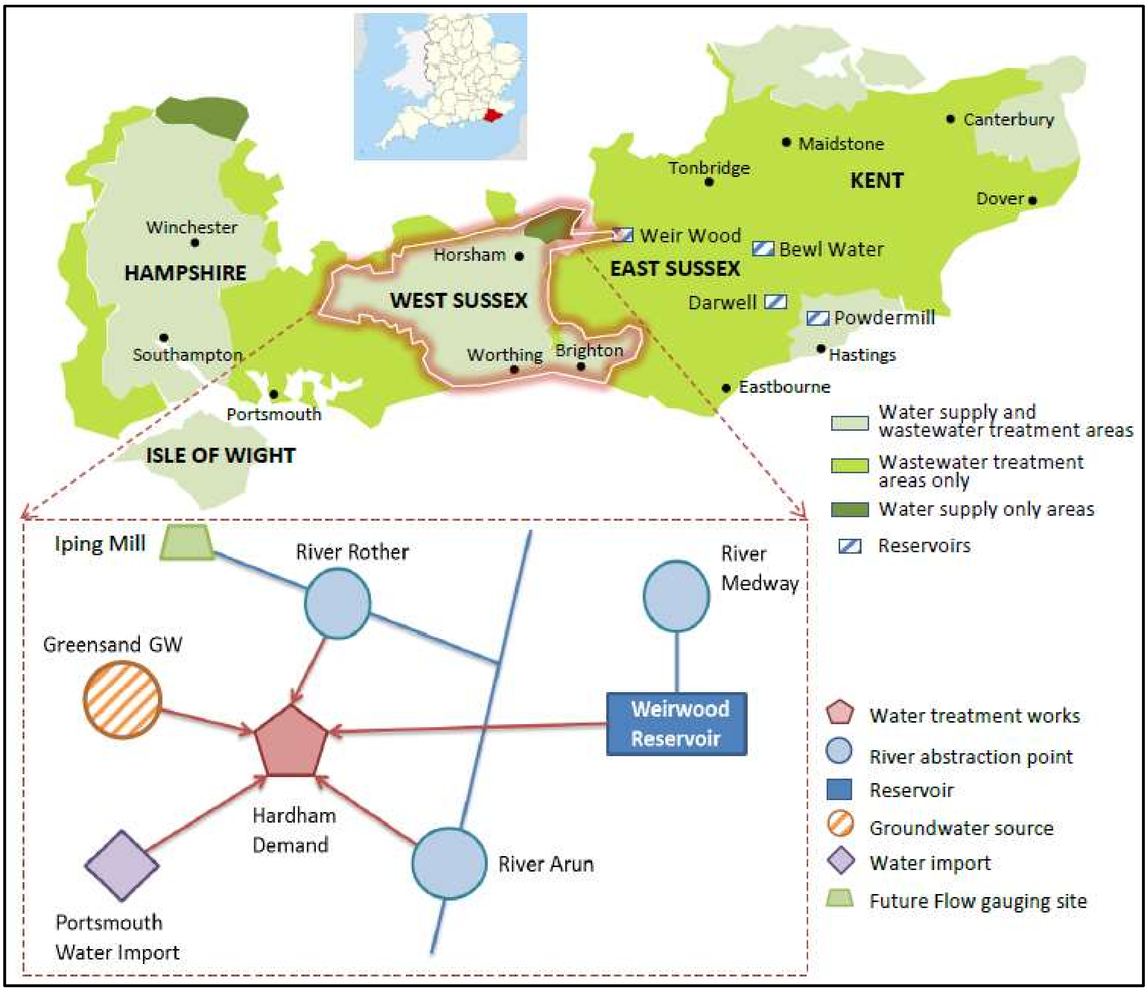

Figure 5.1: Southern Water: Sussex North Water Resource Zone (SNWRZ) and surrounding territories, including network schematic (adapted from Southern Water, 2014; 2015)

Table 5.2: SNWRZ existing water resources

Resource abstraction priority	Resource description	Minimum deployable output (MDO) In ML/d	Projected by Southern Water to be affected by climate change?
1	River Rother/Arun abstraction	40[a]	Significantly
2	Groundwater sources	11.05[b]	Not significantly
3	Portsmouth water import	15[b]	Not significantly
4	Reserve groundwater at Hardham	36.96	Not significantly
5	Weir Wood reservoir storage	21.82	Significantly

[a]Dependent on minimum residual flows (MRFs) in the river Rother
[b]Set at a constant value

Water from all sources is treated at the Hardham Water Treatment Works (WTW). The minimum deployable output (MDO), which defines the water resource availability at the point at which it is most physically constrained and typically occurs in early autumn before the onset of winter recharge, is used to define the availability of new resource options (Southern Water 2009; 2014). The priority order for abstraction of each resource (shown in Table 5.2) is based directly on the SNWRZ system order (Southern Water, 2009). On each daily time step of the simulation model – river abstraction occurs first and reservoir abstraction last in order to meet the required demand. This allows the reservoir resource to remain as reserve storage until required (e.g. when demand levels are high or river flow levels are low).

The aim of the WRM problem analysed here is to, over a 50 year planning horizon, determine the best adaptation strategy(ies) to implement within the existing regional WRM system that will *maximise* the robustness of future water supply whilst *minimising* the total cost of interventions required (as defined in equations (4.1) and (4.6) respectively).

5.3.2 Case study set-up

The dynamic water resource simulation model (described in section 4.3) is set up for the SNWRZ to simulate the daily supply-demand balance of the water system over a 50 year planning horizon (2015-2064 inclusive). A 50 year planning horizon has been selected to incorporate more climate change and demand uncertainty over time than a typical 25 year UK water company planning horizon.

5.3.2.1 Adaptation strategies

A list of new potential water supply resources for the SNWRZ was taken from Southern Water's WRMP 'feasible' options list (Southern Water, 2009). This included the range of options derived from the final phase (Phase 3) of resource investigation and appraisal carried out by Atkins (2007). This created a pool of potential intervention options (see Table 5.3), from which adaptation strategies can be formed by implementing different combinations of the new supply options, arranged over the 50 year planning horizon. The planning horizon is further sub-divided into 10 year construction periods, producing five potential operational start points for each option within a strategy. This is to reduce the number of potential combinations of strategies, allowing swifter optimisation and easier pre-selection of strategies for the application of IG methodology.

The total cost of a strategy is calculated using the Present Value (PV) approach shown in equation (4.6), with an assigned annual discount rate of 3%, as utilised by Southern Water (2009). The variation in water treatment costs of each individual resource option are included in the calculation of projected operational costs; however the uncertainties in changing water resource quality and the changing operational costs of individual options over time are not incorporated in this investigation due to low available data on these aspects. It should be noted that energy and water treatment costs are also highly variable and liable to change over time, but these uncertainties are beyond the scope of this investigation. The intervention options in Table 5.3 include the list of potential new 'supply' additions to the system. Demand side options are also important considerations for addressing the supply-demand balance. However, due to the Sussex North Water Resource Zone being classified as a "serious water stress area" (Environment Agency, 2007; 2013b), compulsory Universal Metering (UM) of all properties has already been initiated and a set leakage program is underway, therefore further demand side options are not included as potential intervention options in this analysis. New resource options (Table 5.3) are implemented in the simulation model between existing supply resources 3 and 4 (Table 5.2). This allows reserve groundwater and stored water at Weir Wood reservoir to remain as storage until required.

Table 5.3: New water resource supply options available for the SNWRZ

Option	Resource option description	Minimum deployable output (ML/d)	Estimated capital costs (£M) (2015)	Estimated annual operational costs (£M/yr) (2015)
A	Surface storage reservoir with combined river Rother/Arun feed	26	47.8	0.21
B	Effluent re-use Scheme-MBR at Ford WWTW	19	36.7	0.16
C	Tidal river Arun desalination plant - 20ML/d	20	34.6	0.34
D	Tidal river Arun desalination plant - 10ML/d	10	24	0.27
E	Hardham WTW winter transfer to coast	4	17.1	0.12
F	River Adur abstraction point	5	11.2	0.07
G	Aquifer storage on the Sussex coast	5	10.8	0.06
H	River Arun abstraction point (below tidal limit) and small storage reservoir	11.5	10.2	0.07
I	Winter refill of Weir Wood reservoir	3	3.2	0.02

5.3.2.2 Supply scenarios

In this analysis the application of using Future Flow scenarios (Prudhomme et al., 2012) to generate future projections for the region's major contributing river flows and reservoir inflows is used as outlined in section 4.4.1. The closest Future Flow gauging site for Sussex North is at Iping Mill on the river Rother upstream of the Hardham extraction point (see Figure 5.1). The flow data required downstream of the gauging station are translated using the monthly rolling flow factoring method as outlined in section 4.4.1 and then resampled five times including one unchanged base-case. The 11 flow factors are then used to perturb the historic resampled river flow data at Hardham (Figure 5.1) to provide 72 discrete supply scenarios. The same flow factors were used to perturb the inflows to Weir Wood reservoir and flows in the River Arun to ensure the system is modelling the same patterns of weather and climate change throughout the system at the same time. The reliability of future groundwater and imported water from the Portsmouth region are not projected to be significantly impacted upon by the regions climate change projections so their current MDO values are taken as consistent daily inputs to supply over the full planning horizon (Southern Water, 2009).

5.3.2.3 Demand scenarios

Demand Scenarios for the Sussex North region have been produced using data from Southern Water's WRMP 2010-35 (Southern Water, 2009), which includes data to 2035 that is then extrapolated to 2060 using the same rate of change increases as those within the 2030-2035 data, as recommended by Southern Water (2009; 2014). They consist of four scenarios based on varying success levels following the enforced introduction of Universal Metering (UM) in the region (see Table 5.4). This requires full metering of all properties and non-household businesses by 2015 and the scenarios illustrate the projected effect of this introduction from a pessimistic demand increase to more optimistic results and also include scenarios of low leakage increases and high leakage increases following the implementation of the regional leakage program (Southern Water, 2009).

Table 5.4: Demand scenarios for the SNWRZ (ML/d)

Scenario name	Year beginning – average daily demand[a] (in ML/d)									
	2015	2020	2025	2030	2035	2040	2045	2050	2055	2060
UM (pessimistic)	69.7	69.6	69.8	70.4	71.0	71.6	72.3	73.2	74.1	75.2
UM (optimistic)	67.2	67.5	68.2	69.2	70.1	70.9	71.8	72.5	73.2	73.8
UM (low leakage)	67.1	67.3	67.9	68.7	69.4	70.2	70.7	71.3	71.7	71.9
UM (high leakage)	68.7	69.0	69.5	70.1	70.9	71.6	72.6	73.7	75.1	76.7

[a]Demand values are the Dry Year Annual Average (DYAA) levels which are then fluctuated monthly throughout each year based on seasonal demand ratios (Southern Water, 2009)

The annual demand projections (in 5 year intervals) given in Table 5.4 are interpolated to produce yearly average demands. The annual average demand is then multiplied by monthly factors to reflect the changing seasonal demand averages employed by Southern Water (2009; 2014). These values are then used to create four 50 year daily time step demand scenarios.

5.3.2.4 Level of system performance

Each adaptation strategy that is tested in the simulation model over a given future scenario combination of supply and demand projections will result in a specific risk of a water deficit estimated (equation (4.2)). For the SNWRZ this risk level (as described in section 4.2.2.2) is calculated once all supply sources have been maximised, with the system entering a ‘water deficit’ (see section 4.2.2.1) when the last source, Weir Wood reservoir reaches a threshold level of 1155 ML (Southern Water, 2009). The likelihood and magnitude of water deficits (calculated as a single risk metric, equation (4.2)) must not exceed a target level of system performance (r_c). This target level of system performance has been determined by calculating the risk of a water deficit occurring over the previous 50 years of historic data. As the system has been deemed acceptable by customers over this period (Southern Water, 2009), maintaining the system at its current level of historic risk is considered as acceptable system performance. The existing system, when tested in the simulation model with historic flows/inflows, recorded 20 days of water deficits over the 50 year period (18,263 days) and registered a total combined water deficit of 388 ML. Applying equation (4.2), this resulted in the target level of system risk (r_c) of 0.425 ML.

5.3.2.5 Application of RO and IG methods

For application of the RO methodology the dynamic, daily-time step, water resources supply and demand simulation model is combined with the NSGA-II optimisation algorithm (as described in sections 4.3 and 4.5.2). The NSGA-II algorithm parameters used (derived following testing of numerous combinations to ensure true Pareto optimality is obtained) are as follows:

Table 5.5: NSGA-II parameters selected

Parameter	Value
Population size	200
Number of generations	500
Selection bit tournament size	2
Mutation probability (per gene)	0.2
Crossover probability (single point)	0.7

Adaptation strategy generation, testing, ranking, mutation and ultimate Pareto optimal strategy identification is an automatic process carried out by the NSGA-II algorithm during the RO procedure after 500 generation assessments. Ten separate runs (random seeds) are tested to ensure that the true Pareto optimal strategies are being identified by the optimisation process.

For the application of the IG methodology, multiple adaptation strategies are manually pre-specified from the range of potential intervention option combinations and evaluated using the IG robustness model created. For this study complete enumeration (generation of all possible strategy combinations) was not utilised as this approach yielded too many combinations for feasible computational testing. Hand picking a small number of “preferred” strategies for testing (i.e. based on Southern Waters preferred strategy lists (Southern Water, 2009, 2014)) was also not a suitable approach as it greatly limits the number of strategies evaluated making the decision process highly subjective. Therefore a random sampling approach was utilised, whereby a set number of strategy combinations were selected at random constrained by a rational list of assumptions. These assumptions were based on information from Southern Water’s WRMP 2010-2035 (Southern Water, 2009) and included:

- Limiting the PV of total cost of adaptation strategy to £120 million over the planning horizon.
- A minimum of 10 ML/d to be added to the system over the planning horizon.
- Intervention options C and D cannot be combined in the same strategy.
- Intervention options that provide more deployable output for less cost than alternative options should have priority of construction (e.g. option G should be employed before F; option H should be employed before options D, E, F and G). However, the superseded options can still be employed in combination with their superior counterparts either at the same time or at a later point in the planning horizon.

A random sample generation tool was developed in Python to select the set of adaptation strategies for testing. The tool generated 28,000 individual adaptation strategies (of different intervention option combinations and varying sequencing of the options across the time horizon) for application to the methodology detailed in section 4.5.1. Each adaptation strategy was then evaluated using the IG robustness model. The resulting strategy robustness vs cost results are then ranked to identify a set of IG Pareto optimal strategies. This is a non-traditional step in the IG process; however, it allows for easier comparison of the two DMMs.

5.3.3 Results and discussion

For each DMM the 72 supply and 4 demand scenarios (i.e. a total of 288 possible scenario combinations) were modelled with the adaptation strategies, leading to the identification of Pareto optimal sets for both decision making methods (RO and IG(U_{mid})), trading-off the robustness of water supply and the PV of total cost (see Figure 5.2).

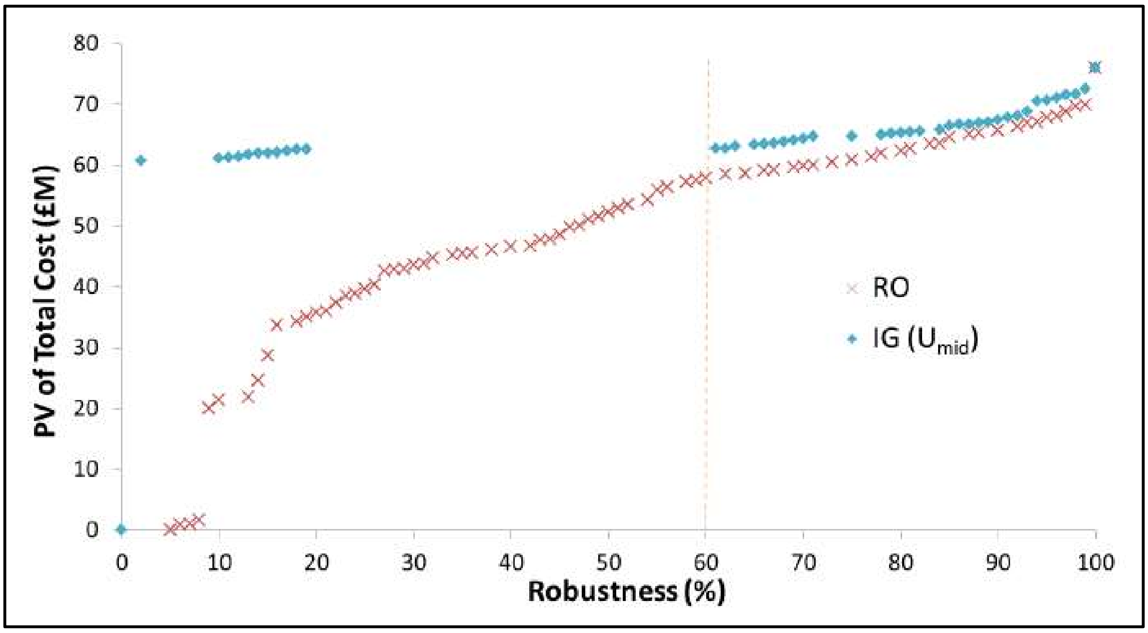

Figure 5.2: Pareto sets identified by the info-gap and robust optimisation methods

IG(U_{mid}) indicates that the Info-Gap analysis began from the median scenarios of supply and demand (following scenario severity rankings as stated in section 4.5.1). As it can be seen from Figure 5.2, when compared to RO, the IG method always produces higher-cost Pareto strategies for the same robustness level. The distribution of Pareto strategies across the range of robustness is also lower for the IG analysis, with no Pareto strategies recorded between 20-60% robustness levels. The reason for both occurrences is due to the IG's local robustness analysis and the method of ordering the scenarios. Examining the uncertainty region from a local point outwards requires multiple-adjacent scenarios to be satisfied in order for the robustness search to continue. This leads to more stringent localised performance requirements than those placed on global robustness. As the analysis expands outward in an area calculation of satisficing scenarios, occasionally imperfectly ordered scenarios can lead to isolated regions of much higher requirements, which can pre-maturely end the robustness analysis. The reason for this is that several scenarios beyond these regions may have been satisfied by a strategy had they been reached. Figure 5.3 depicts a simplified example of this 'blocking' effect using two example scenarios.

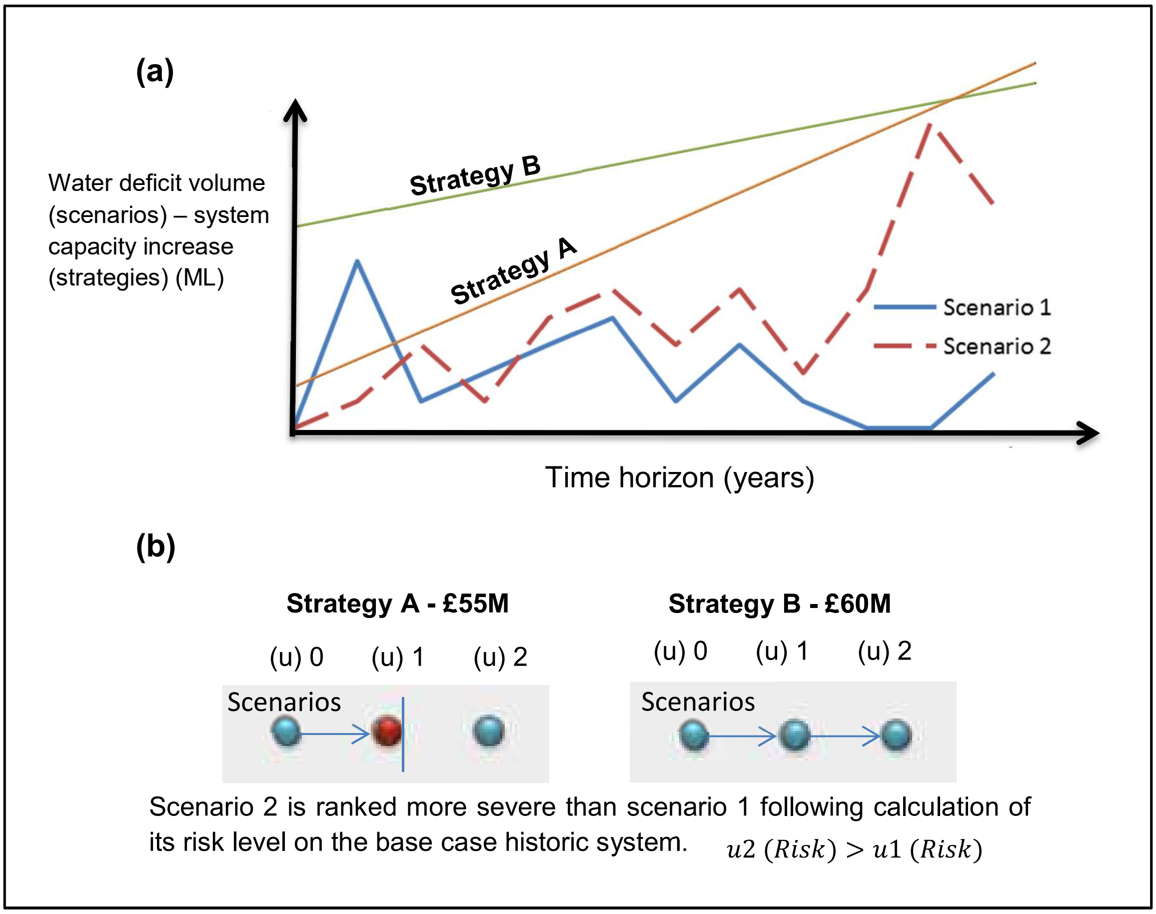

Figure 5.3: (a) Example of a scenario ordering arrangement that would prematurely end an info-gap robustness search, explained via two scenario water deficit profiles and the respective system capacity increase provided by two adaptation strategies; (b) Strategy A has not satisfied scenario 1 but would have satisfied scenario 2, Strategy B has satisfied both scenarios but for increased total cost

The scenario profiles illustrate the changing water deficit levels projected on the current water system over time. Both scenarios are projecting frequent deficits across the planning horizon if the system is not adapted; however, scenario 2 is calculated as having the higher risk of water deficit value (equation (4.2)) over the planning horizon, so is ranked and ordered as more severe than scenario 1. When example strategy A is tested over scenario 1 the system fails as the risk of water deficit exceeds the target level of system risk. However, it would have satisfied scenario 2, but this scenario is not examined as the IG assessment is terminated following failure to satisfy scenario 1. Consequently, IG theory would favour strategy B as it provides a sufficient system capacity increase to satisfy both scenarios, but has a trade off as being the more expensive one. RO's global assessment incorporates each successful scenario (e.g. scenario 2 for strategy A) in the robustness calculation regardless of severity ordering and so can more easily satisfy target robustness levels.

Figure 5.3 highlights the difficulty in ordering discrete scenarios into a range of severity, when the individual scenarios are so variable and complex in their constituent parts (i.e. including 50 year river flow sequences). This presents a potential weakness of utilising an ensemble of discrete projections for scenario generation with the IG method. Matrosov et al. (2013) tackled this issue by using continuous variables of monthly perturbation factors that diverged out from their median flow factor set at structured intervals, whereas Hall et al. (2012a) adopted an ellipsoid uncertainty model combined with an interval-bounded model to uniformly scale the uncertainty. However, these approaches did not utilise discrete transient flow sequences when forming their scenarios, which was a specific investigative area selected for examination here.

The IG results obtained (see Figure 5.2) also indicate that a strategy of do nothing (i.e. spending £0) produces a 0% robust system and a sharp increase (spending over £60 million) is required to gain just a 2% robust system. This is due to the IG analysis using the median severity scenarios of supply and demand as a starting point, placing numerous hard to satisfy scenarios in direct proximity to the starting location. However, it could be argued that a solution of low robustness is not desirable so only the solutions of higher robustness (i.e. the IG results >60% robustness in Figure 5.2) are significant to the final decision maker.

Figure 5.4 presents the breakdown of intervention options within all the Pareto strategies ranked above 60% robustness for both RO and IG methods. It shows the percentage of Pareto strategies that feature each option (a), including graphs showing the year of construction of each option as a percentage of occurrences, for the RO (b) and IG (c) Pareto strategies.

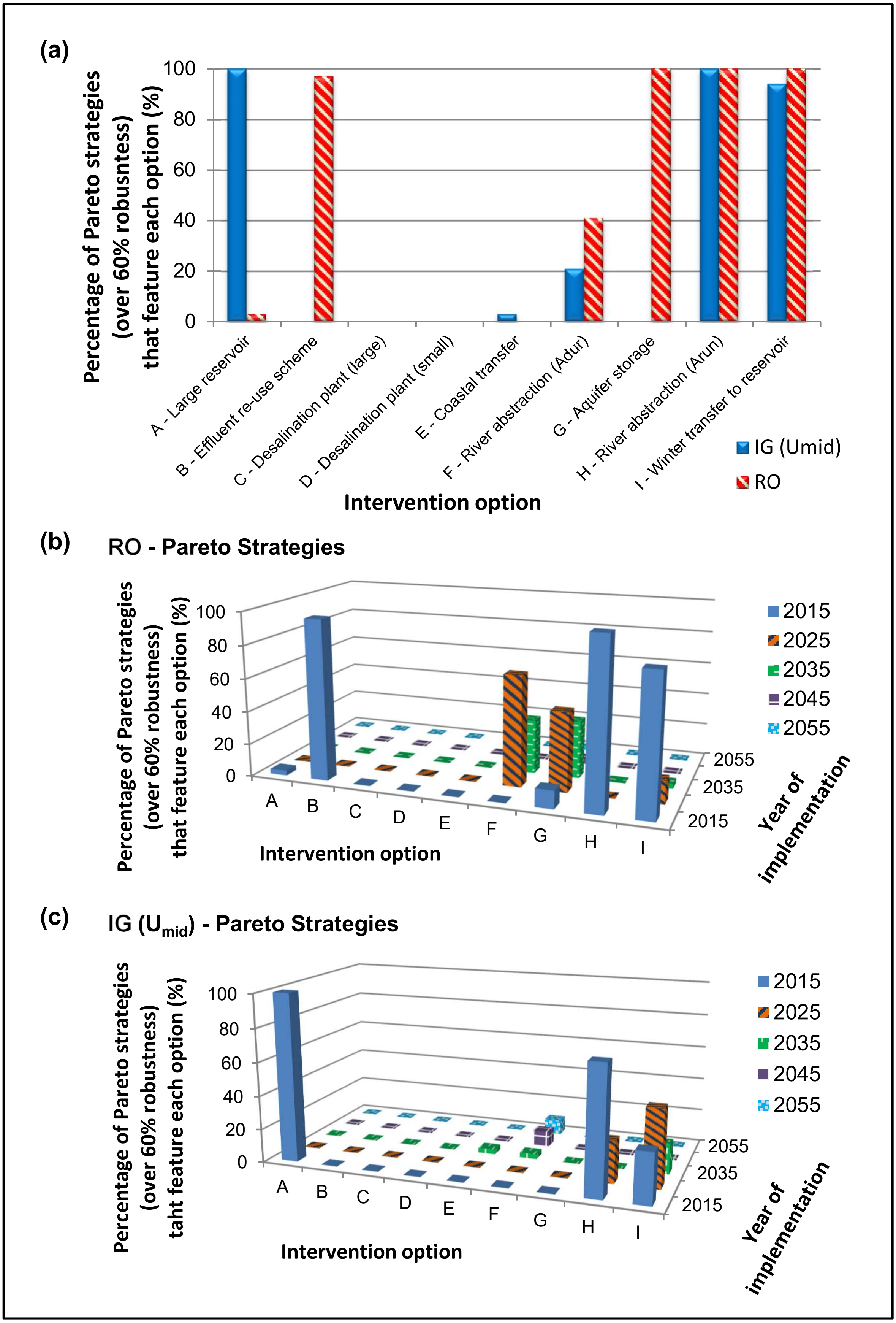

Figure 5.4: (a) Individual intervention options that feature in the Pareto strategies ranked above 60% robustness for info-gap and robust optimisation methods as a percentage of occurrences; and their year of implementation (also as a percentage of occurrences) for the RO (b) and IG (c) Pareto strategies

It highlights several interventions as being the most cost-effective options following their inclusion in all the Pareto strategies (e.g. option H – a new river Arun abstraction point including a small scale storage reservoir; and option I – a new pipeline for transfer of excess winter water to refill Weir Wood reservoir). Both DMMs have identified Pareto strategies that sequence the majority of intervention options early in the planning horizon (2015-2035). The main difference between the IG and RO Pareto strategies is IG's regular selection of a large new reservoir (option A) to be constructed immediately in the planning horizon (2015) to increase overall system robustness (explained previously via Figure 5.3), whereas RO repeatedly selects option B (an effluent re-use scheme) in 2015, providing less water than option A but for less initial cost earlier in the planning horizon. The RO strategies then sequence additional options G and/or F (aquifer storage and a new abstraction point on the river Adur) later in the planning horizon to increase water supply as more frequent deficit periods are projected over time.

Neither method selects a desalination plant (option C or D), most likely due to the high operational cost of this supply option. In general the IG method tends to favour fewer, but larger scale intervention options scheduled early in the planning horizon, compared to the RO method, which frequently selects more but smaller scale intervention options more evenly spaced across the planning horizon. This is again due to the more stringent robustness analysis requiring a wide range of scenarios to be sequentially satisfied in the expanding local robustness "search", as discussed in Figure 5.3.

The IG pre-specified adaptation strategy generation process, using random samples rather than full enumeration, did not contribute to a difference in the Pareto strategies identified as significantly as expected, as the majority of RO Pareto strategies were also found among the IG pre-specified selection. Although, RO was able to identify several strategies that were not among the pre-specified set used in the IG analysis. The low impact of the strategy generation process is likely due to this case study's relatively small pool of intervention options examined and using a planning horizon segmented into 10 year construction periods. This allowed the majority of strategy combinations to be generated during the random sample generation process. It is expected that a more complex case study with a larger pool of potential options will lead to more variation in the final Pareto strategies identified – this is an aspect for further investigation (see section 5.4).

Figure 5.5 presents the Pareto strategies selected by the IG robustness analysis following variation of the initial starting point of the robustness analysis (U_{high}, U_{mid} and U_{low} in the scenario severity index). It reveals that the variation of start point did not alter the final Pareto strategies identified significantly, as can be seen by the largely overlapping IG Pareto fronts. The main variation can be seen in the strategies identified below 50% robustness, where lower costing strategies are more readily identified by U_{low}. This is because the larger robustness areas will encompass all the starting points regardless of their location within the region of uncertainty; however strategies of lower robustness will be identified at a more cost effective rate from a lower severity start point. This also implies that the starting point becomes increasingly important the larger the uncertainty region becomes.

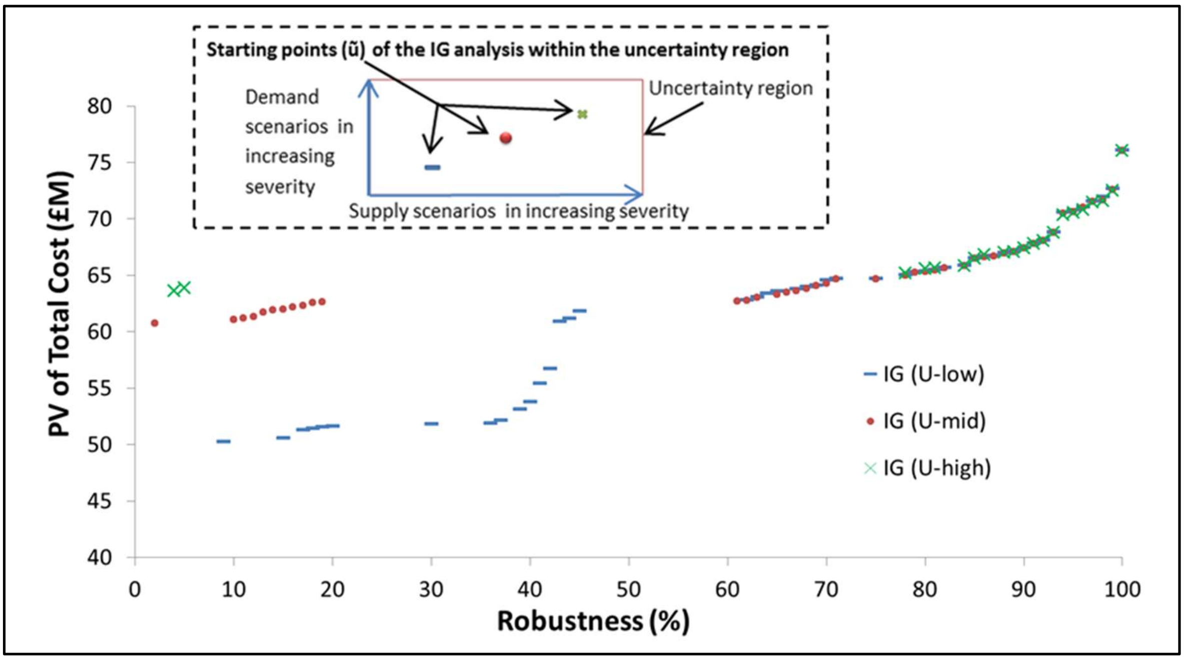

Figure 5.5: Pareto strategies identified by Info-Gap following variation of the initial start point of the analysis (denoted as U_{high}, U_{mid}, and U_{low})

Southern Water's current water resource adaptation plan for the Sussex North WRZ (Southern Water, 2009; 2014) includes option H (a new river Arun abstraction point including a small scale storage reservoir) which has been constructed and is now in use as of 2015, as well as plans for Options I (new pipeline to refill Weir Wood reservoir), G (aquifer storage) and B (the effluent re-use scheme) scheduled for 2018, 2020 and 2026 respectively. These options were also frequently selected within both DMM Pareto strategies; however, the overall plans differ, as both IG and RO produced Pareto strategies recommending a greater system capacity increase to the system earlier in the planning horizon to ensure higher levels of overall system robustness. Although this may seem an obvious statement qualitatively the DMMs provide quantitative information as to the *size of the capacity increase* and *where* and *when* it needs to be added to the existing system to achieve a specific level of robustness.

The larger initial resource options recommended also highlight the effect of examining multiple scenarios rather than planning to a single projection of supply and demand. The current UK industry planning methods assume a linear scaling of climate change between present day and the end of the planning horizon (Environment Agency et al., 2012) that ignores the variability from droughts, which these methods explicitly capture in this study. Therefore, by varying climate change and droughts you naturally plan for a wider range of robustness. It could also be argued that current methods do not evaluate for robustness given they typically only use central deterministic scenarios. The 5 year cycle of water company WRMPs also means that large investments are typically deferred whilst low impact, low costs measures are implemented, as it is very hard to get large infrastructure development past the regulators. The more substantial resources recommended early in the planning horizon by both DMMs highlight these potential issues in current practice. The results could also be linked with the longer planning horizon considered in this assessment, whereby higher initial costs are traded for greater long term system robustness – an aspect for further investigation (see section 5.4). The selection of the most suitable risk-based (or individual criterion) metric as well as an appropriate selection of target system performance, are also likely to heavily influence the final Pareto strategies obtained.

Computational aspects of the methods (coding complexity and computational time) have not been examined in detail in this study as the computational set-up is considered very specific to this case study and to the specific approaches developed here.

5.3.4 Conclusions

The Robust Optimisation and Info-Gap methods were applied and compared on a case study of the Sussex North Water Resource Zone in the UK with the aim to solve a specific WRM problem driven by the maximisation of robustness of long-term water supply and minimisation of associated costs of adaptation strategies, all under a range of uncertain future supply/demand scenarios. The results obtained lead to the following key conclusions:

1. The two DMMs analysed produced different Pareto adaptation strategy recommendations to each other and to the strategies derived using the current UK engineering practice.
2. Robust Optimisation generally produced lower costing Pareto strategies than IG for all ranges of desired system robustness due to RO's less stringent method of global analysis, i.e. not needing to satisfy adjacently ranked scenarios for the robustness analysis to continue.
3. Info-Gap's local analysis proved problematic to construct and assess using discrete scenarios and likely contributed to the higher costing strategy recommendations.
4. Optimisation, although not applied to the IG methodology here is likely to be required at some stage of planning when dealing with larger data sets and a larger pool of potential intervention options.
5. The location of the starting points of the IG analysis did not significantly alter the Pareto strategy results obtained, especially at higher robustness levels. However this could be associated to case study complexity and should be examined on more complex case studies to further explore this pivotal aspect of the theory.
6. The variation in the Pareto strategies derived highlight how the current industry standard for water supply system adaptation planning could benefit by applying a wider range of decision methodologies and assessment tools (especially those that quantify a level of system 'robustness') as well as a more encompassing investigation into potential future uncertainties and alternative methods for scenario generation.

It is recommended that further analysis of IG and RO methods be undertaken on more complex case studies, utilising a larger pool of intervention options and a greater number of scenario projections before above conclusions, including computational conclusions on the DMMs, could be generalised. This was done in the following text.

5.4 Bristol Water case study

This section aims to compare the contrasting mechanisms and outputs of two DMMs analysed (Info-Gap and Robust Optimisation) on a more complex real-world WRM case study then previously studied (section 5.3). The study again assesses the applicability of using "*prospective*" transient supply and demand scenarios in the form of Future Flows climate/hydrology projections, but differs in its use of an individual criterion of "system reliability" to measure water system performance in place of a risk-based measure. This allows a more direct comparison of the current EBSD 'levels of service' method utilised by BW in generating their proposed plan for 2015-40 (Bristol Water, 2014). The adaptation strategy solutions derived by the two DMMs are compared with the real-life BW plans derived from current industry practice, before finally comparing the Pareto strategies derived using a 25 year planning horizon with those identified by using a 50 year planning horizon.

5.4.1 Case study description

The methodology detailed in Chapter 4 is applied to a case study of the Bristol Water Resource Zone (BWRZ). A region in the south-west of the UK supplying approximately 1.2 million customers (as of 2015), which is expected to experience increasing pressures on local water resources from rising populations (with a 15% projected increase in demand by 2045) and increased climate variability that could cause further reductions in the availability of established resources. Should no adaptations be made to the system in the near future (new water supply additions etc.) then the system is projected to suffer significant shortfalls in its ability to meet demands by 2020, as illustrated in Figure 5.6 (Bristol Water, 2014).

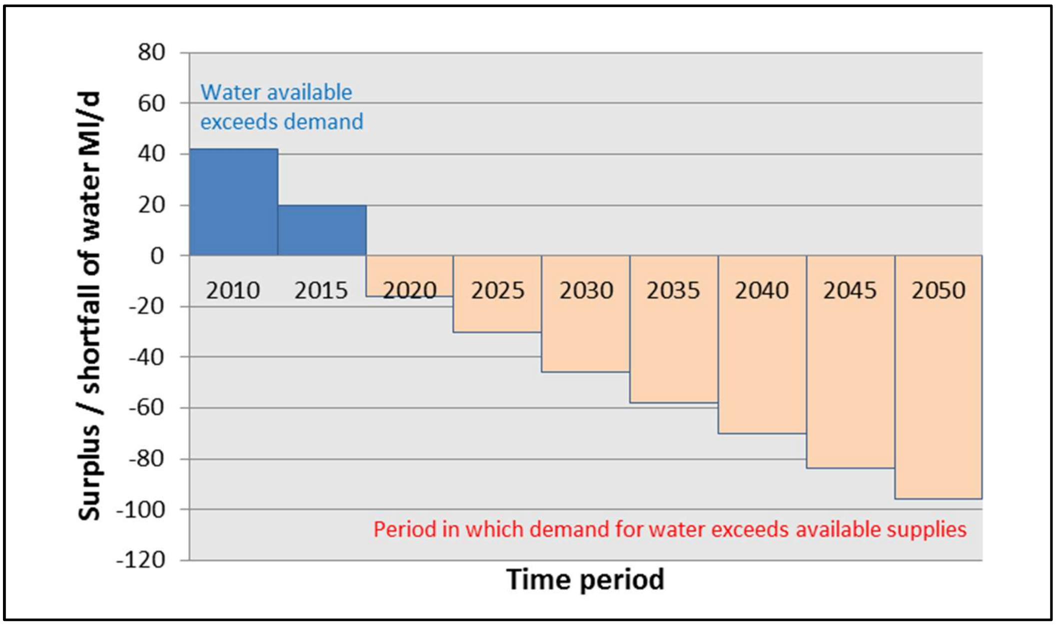

Figure 5.6: Bristol Water projected supply-demand balance without adaptation measures (adapted from Bristol Water, 2014)

The main existing water resources are shown in Figure 5.7 and listed in Table 5.6. They consist of a variety of sources, with approximately half of the required supply coming from the River Severn (via the Sharpness canal); a third from reservoirs fed from the Mendip Hills; and the remainder from small wells and springs throughout the supply area (Bristol Water, 2014).

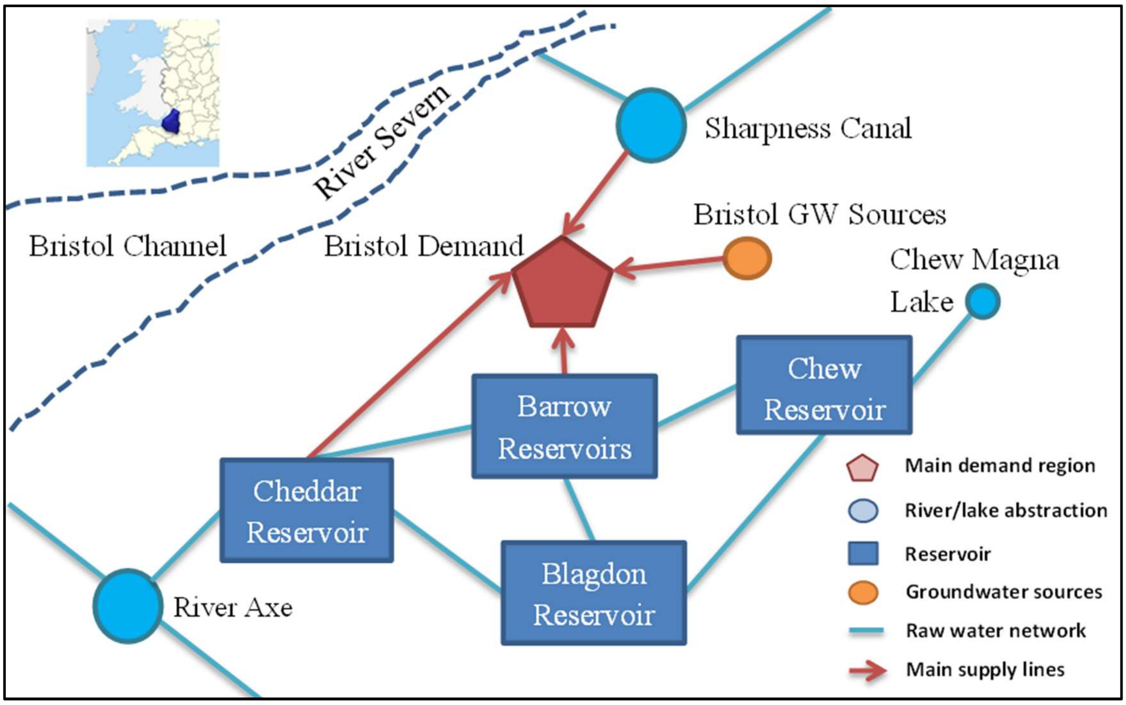

Figure 5.7: Bristol Water Resource Zone (BWRZ) schematic

Table 5.6: BWRZ existing water sources and abstraction priority ordering (Bristol Water, 2014)

Resource abstraction priority	Resource description	Deployable output[a] (DO) annual average - in ML/d	Projected by Bristol Water to be affected by climate change?
1	Sharpness canal	210	Not significantly
2	Groundwater sources	65	Not significantly
3	Mendip reservoirs	91	Significantly

[a]DO is the yield of the source subject to additional system constraints such as the abstraction license, infrastructure capacity and environmental requirements.

The BWRZ is based upon the operation of the company area as a single resource zone. This means that all water resources (river, groundwater and reservoirs) within the company area are capable of being shared throughout the zone at all times of the year via a comprehensive pipe transfer network and using multiple water treatment works, as shown in the Mendip reservoirs network schematic in Figure 5.8 (Bristol Water, 2014). In this way, no part of the zone is solely dependent upon the yield of a single water source. This has been the approach adopted in previous BW WRMPs and agreed as appropriate for the current 2014/15 plan with the Environment Agency (Bristol Water, 2014).

The priority order for abstraction of each resource (shown in Table 5.6) is based on the BWRZ system priority of use. The primary river and groundwater sources are considered reliable and sustainable over the next planning period (2015-2039 inclusive); whereas the resource available from the network of Mendip reservoirs is anticipated to be impacted by climate change.

There are three main components to the reservoir system to be modelled when projecting climate scenarios. These are: the Mendip catchment region (direct reservoir inflows); the river Axe at Cheddar and the lake at Chew Magna (see section 5.4.2.2).

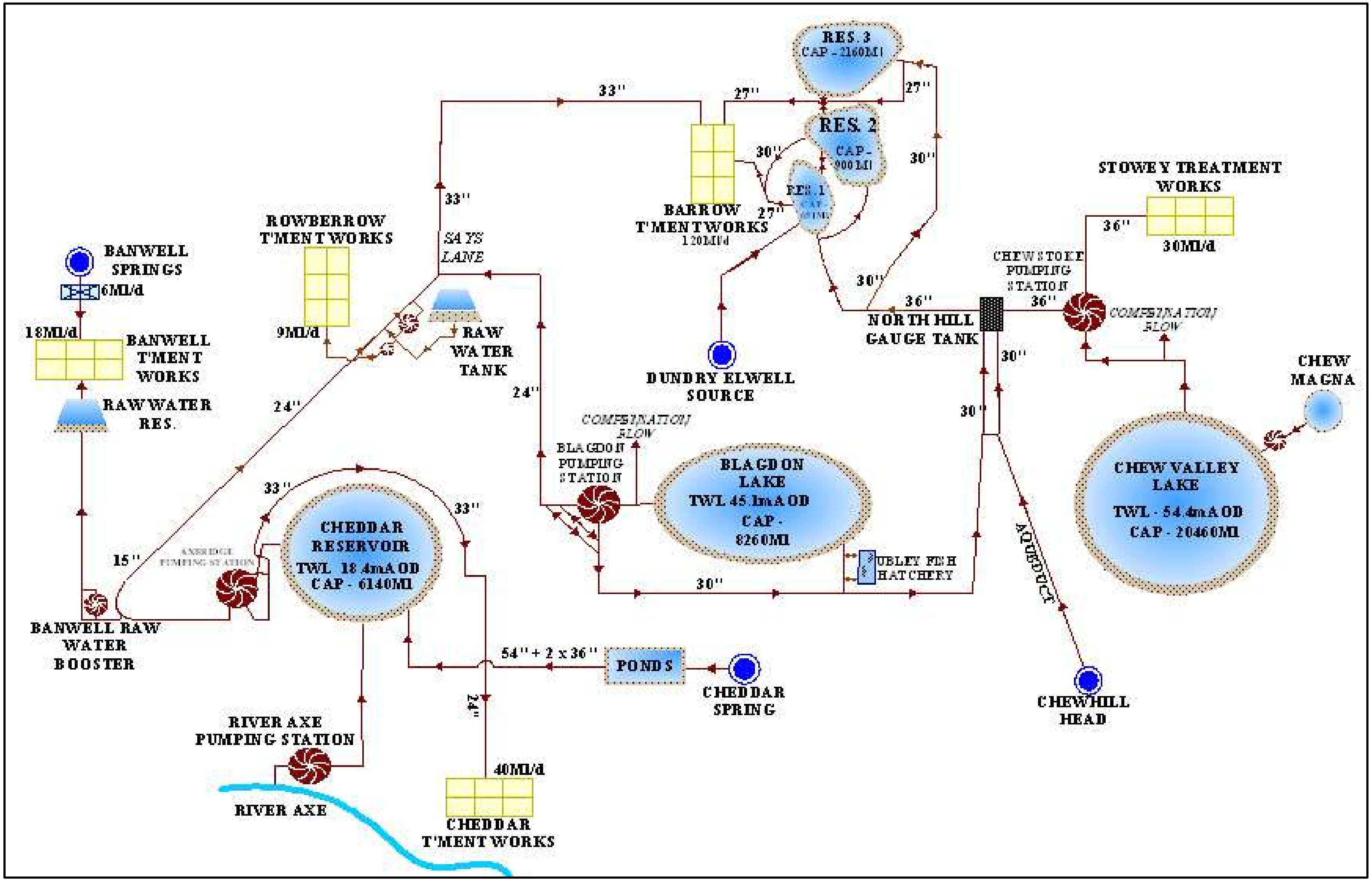

Figure 5.8: Bristol Water: Mendip reservoirs network schematic (Bristol Water, 2014)

The aim of the WRM problem analysed here is to, over a 25 year planning horizon, determine the best adaptation strategy(ies) to implement within the existing regional WRM system that will *maximise* the robustness of future water supply whilst *minimising* the total cost of interventions required (as defined in equations (4.1) and (4.6) respectively).

The dynamic water resource simulation model (described in section 4.3) is set up for the BWRZ to simulate the monthly supply-demand balance of the water system over a 25 year planning horizon (from year 2015 to year 2039 inclusive). A 25 year planning horizon has been selected to imitate the time frame used in a typical UK water company WRMP planning horizon. However, a 50 year planning horizon is also tested to analyse the effect on intervention selection from altering the planning horizon length.

5.4.2 Case study set-up

The dynamic water resource simulation model (described in section 4.3) is set up for the Bristol Water resource zone to simulate the monthly supply-demand balance of the water system over a 25 and 50 year planning horizons. All BW data files utilise a monthly time step, hence a monthly time step has been implemented in this case study.

5.4.2.1 Adaptation strategies

An investigation into potential new water supply resources and options to reduce water consumption/losses was carried out using data surveys for the Bristol Water region (Bristol Water, 2014). This created a list of potential intervention options (Table 5.7), from which different intervention (i.e. adaptation) strategies can be formed by implementing combinations of options arranged over a strategic planning horizon (e.g. 2015-2039). The total cost of strategies is calculated using the Present Value (PV) approach shown in equation (4.6), with an assigned annual discount rate of 4.5%, as utilised by Bristol Water (2014).

The options C4, D1, D4, and D6 (see Table 5.7) feature in the BW WRMP 2015-40 as planned interventions for 2015. Hence, for this study it is assumed that these interventions will be put in place from the start of the planning horizon and included them in all adaptation strategy assessments. An additional outgoing supply of 19 ML/d of non-potable water to new customers in Avonmouth is also scheduled to begin in 2018 so has been incorporated in the water resource model from this time period onwards.

The variation in water treatment costs of each individual resource option are included in the calculation of projected operational costs; however the uncertainties in changing water resource quality and the changing operational costs of individual options over time are not incorporated in this investigation due to a lack of available data on these aspects. It should be noted that energy and water treatment costs are also highly variable and liable to change over time, but these uncertainties are beyond the scope of this investigation.

Each intervention option will also carry a level of uncertainty in their projected deployable output (DO). However, a single fixed daily DO has been assumed for this study to simplify the optimisation and because there are no inflow data and operational rules in order to model the effects of climate variability for the option locations. The day to day operational rules used by BW allow a more dynamic control of output from specific options at given times of the year in order to reduce operational costs of higher energy resources, but these variables were not included in the following methodology due to the use of a simplified water resources model. In practice it is recommended that simplified water resources models are used for higher level adaptation strategy appraisal, in order to identify subsets of scenarios and system configurations which are then tested using a more detailed operational model, which are typically more computationally intensive.

New supply resource options (see rows R1-R18 in Table 5.7) are implemented in the simulation model resource order between existing supply resources 2 and 3 (Table 5.6).

Table 5.7: Intervention options available for the Bristol Water region (Bristol Water, 2014)

Option code	Intervention option	Capital cost (£M)	Operational cost (£M/year)	Deployable output (DO) (ML/d)
	OPTIONS TO REDUCE WATER CONSUMPTION			
C1	Smart metering rollout	11.45	0.06	2.6
C2	Compulsory metering of domestic customers	32.32	2.40	8.0
C3	Selective metering of domestic customers (high users)	5.98	0.32	3.2
C4	Selective change of ownership metering domestic customers	32.45	1.45	11.6
C5	Business water use audits	0.00	0.30	1.0
C6	Household water efficiency programme (partnering social housing)	0.00	0.42	0.4
	OPTIONS TO REDUCE WATER LOSSES			
D1	Pressure reduction	2.47	0.01	2.8
D2	Mains Infrastructure replacement	78.47	0.00	2.2
D3	Communication pipe replacement	36.24	0.00	3.4
D4	Communication pipe and subsidised supply pipe replacement	3.51	0.00	2.2
D5	Leakstop enhanced	1.75	0.00	0.2
D6	Active leakage control increase	0.00	0.91	4.4
D7	Zonally targeted infrastructure renewal	165.08	0.06	13.4
	OPTIONS TO PROVIDE ADDITIONAL WATER RESOURCES			
R1	Minor sources yield improvement	14.68	0.32	1.8
R2	City docks to Barrow transfer scheme	179.42	1.87	30.0
R3	Desalination plant and distribution transfer scheme	179.42	1.87	30.0
R4	Cheddar second reservoir	99.67	0.16	16.3
R5	Purton reservoir and transfer scheme	288.57	4.30	25.0
R6	Pumped refill of Chew Valley reservoir from river Avon	153.81	3.40	25.0
R7	Upgrade of disused southern sources	8.30	0.30	2.4
R8	Effluent re-use for commercial and industrial customers	165.75	1.91	20.0
R9	Avonmouth WWTW direct effluent re-use	185.85	2.07	20.0
R10	Severn Springs bulk transfer	100.94	0.89	15.0
R11	Reduction of bulk transfer agreements	0.00	0.30	4.0
R12	Bulk supply from: (Wessex Water Bridgewater)	26.37	2.31	10.0
R13	Bulk supply from: (Vyrnwy via Severn and Sharpness)	151.95	4.29	25.0
R14	Huntspill Axbridge transfer (traded licence)	10.23	0.14	3.0
R15	Honeyhurst well pumped transfer to Cheddar	5.11	0.01	2.4
R16	Gurney Slade well development	10.70	0.26	1.5
R17	Holes Ash springs re-development	10.22	0.02	0.8
R18	Chew Stoke Stream reservoir	54.81	0.17	8.0

5.4.2.2 Supply scenarios

Future flow/inflow scenarios for the three reservoir inflow sources that supply the Bristol Water's reservoirs which are 'significantly' affected by climate change (Table 5.6) are again produced utilising the Future Flow climate/hydrology scenarios (Prudhomme et al., 2012), as outlined in section 4.4.1. The closest Future Flow gauging site for the BWRZ is at Midford Brook. This is a 147.4 km^2 catchment area adjacent to the Mendip region.

The specific time-series flow/inflow data required for each source of water being modelled is translated using the monthly rolling flow factoring method outlined in section 4.4.1, which perturbs the resampled historic flow/inflow data at each site to match the Future Flow changes projected at the Midford Brook gauging site. The historic flow/inflow data for each modelled site are resampled 30 times then perturbed using the 11 future flow factors to generate 330 discrete supply scenarios, including one unchanged base-case.

The same set of flow factors are used to perturb the inflows to the Mendip reservoirs, Chew Magna and the flows in the River Axe for one individual scenario, to ensure the system is modelling the coherent patterns of weather and climate change throughout the system/region. Bristol Water's most recent WRMP (Bristol Water, 2014) indicated that the river Severn fed Sharpness canal and all combined groundwater sources exhibit high deployable output reliability to climate variability over the next 25 years (providing licensed levels of abstraction are upheld). The lack of additional data on these sources mean that the current DO values are taken as constant daily inputs to the supply system over the full planning horizon, which is consistent with BW's projections within this study.

5.4.2.3 Demand Scenarios

Demand Scenarios for the Bristol Water region have been produced using per capita consumption values from the latest Bristol Water WRMP (2014) combined with the Office for National Statistics (ONS) population projections (ONS, 2014b). They consist of three scenarios of Low, Principal and High population growth used to perturb historic demand values, which are calculated subject to three alternative levels of demand uncertainty; based on the 80%, 90% and 100% risk and uncertainty calculations (i.e. the target headroom calculations) derived by BW (Bristol Water, 2014; UKWIR, 1998) (Figure 5.9).

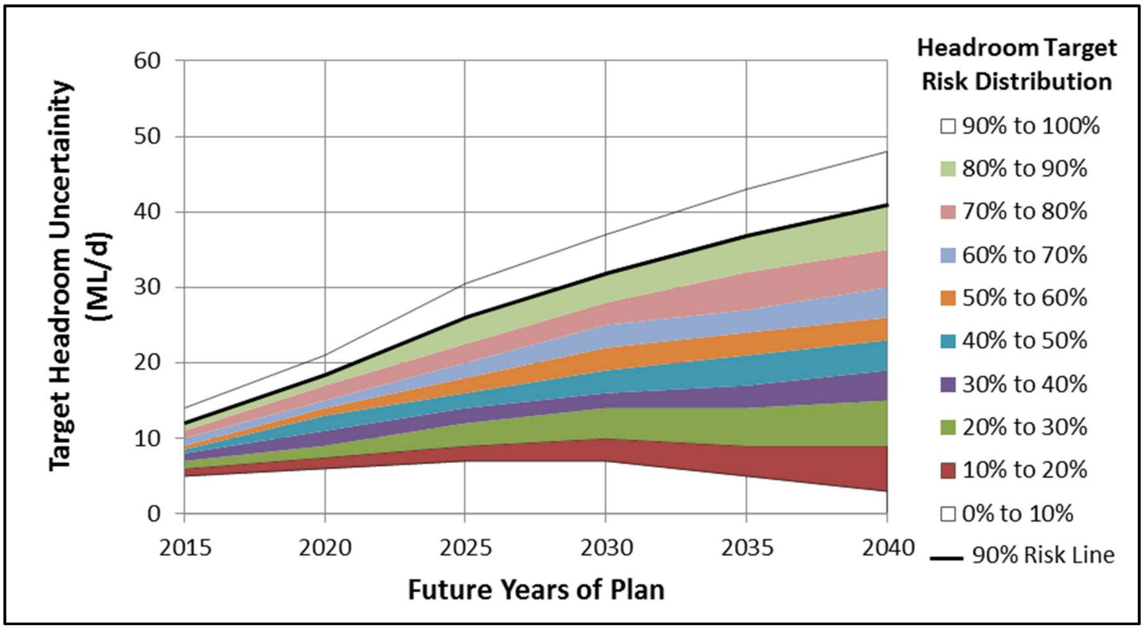

Figure 5.9: Target headroom distributions for Bristol Water – data taken from Bristol Water (2014)

The headroom percentage distributions are calculated either side of the median supply-demand balance forecasts and encompass the plausible range of uncertainty. The target headroom levels utilised were selected as they include the risk and uncertainty percentage level selected by BW for their latest plans (90%) and also the percentage risk and uncertainty levels either side of this selection (80% and 100%), in order to increase the range of demand uncertainty considered. Conventional target headroom estimations also include climate change uncertainties that could affect water supply levels. These values were omitted from the demand scenario generation process as this uncertainty is now explicitly included in the supply scenarios generated.

This approach formed 9 discrete scenarios of demand, which combined with the 331 supply scenarios, creates 2,979 potential future supply and demand scenario combinations to model.

5.4.2.4 Level of system performance

Each adaptation strategy that is tested in the simulation model over a given future scenario combination of supply and demand projections will result in a specific level of reliability (equation (4.3)). For the BWRZ this level of reliability (as described in section 4.2.2.2) is calculated once all supply sources have been maximised, with the system entering a ‘water deficit’ (see section 4.2.2.1) when the last sources, the level of remaining water in the Mendip reservoir network, reaches a given threshold level. The threshold level varies depending on the month of operation and is at its lowest (13,610 ML) in the autumn, rising to a more stringent level (30,000 ML) in the spring. The level of reliability exhibited by the system must not fall below a target level of system performance, i.e. a target level of reliability (r_e).

The current BW WRMP 2015-40 desired 'level of service' (following customer consultation) is to implement temporary use bans no more than 1 in every 15 years (Bristol Water, 2014). Hence over a 25 year planning horizon the system is deemed as operating acceptably if it maintains a reliability of ≥ 92% over the planning horizon and must never reach a magnitude that would induce a water shortage (an empty reservoir network). This reliability level must also be maintained when examining the 50 year planning horizon. The robustness of the water system is then calculated as the percentage (%) of discrete future scenarios under which the system performs acceptably (equation (4.1)).

5.4.2.5 Application of RO and IG methods

The following parameters were selected for the RO NSGA-II algorithm (following testing of numerous combinations):

Table 5.8: NSGA-II parameters selected

Parameter	Value
Population size	400
Number of generations	2000
Selection bit tournament size	2
Mutation probability (per gene)	0.2
Crossover probability (single point)	0.7

It should be noted that increased population and generation parameters were utilised for this case study due to the increased complexity of the Bristol Water problem (larger pool of intervention options available). Adaptation strategy generation, testing, ranking, mutation and ultimate Pareto strategy identification is an automatic process carried out by the NSGA-II algorithm during the RO procedure after 2000 generation assessments.

Due to the greater complexity of this case study, the method of strategy generation for the application of IG theory has been altered from the previous case study. The pre-specified strategy generation process carried out in the Sussex North case study (section 5.3) was achievable due to the relative simplicity of the Sussex North problem, utilising few different intervention options and a planning horizon sub-divided into 10-year construction periods. However, as the Bristol case study is far more complex; with 31 potential intervention options and a planning horizon now sub-divided into yearly construction periods (producing 25 potential operational start points for each option within a strategy - 50 when using a 50 year planning horizon), this produced too many possible combinations of strategies to carry out a reliable process to pre-specify adaptation strategies. Either too many strategies are generated (i.e. using full enumeration) producing an unacceptable model run time, or too few strategies are examined (i.e. using a pre-selection process or random sample generator) making the process overly subjective and reducing the chance of discovering optimal solutions. The number of strategies generated using a random sampling tool can be precisely chosen by the user (as in the Sussex North case study). However, when applied to a complex problem with a large number of potential option combinations the approach ultimately requires too great a number of strategies to be generated to ensure optimal solutions are included. A reduced random sample size of strategies could alternatively be produced, but this reduces the chance of identifying optimal solutions.

For this reason the NSGA-II optimisation algorithm is again utilised. The algorithm tool, set up in the R-programming language (R Core Team, 2013), is wrapped around the combined dynamic water resource simulation model and IG robustness mapping model (see section 4.5.1) and set up with the same optimisation parameters listed for the RO method above. This allows an early conclusion to be established from this case study, recognising that a more complex case study, utilising a large number of potential intervention options, will require some form of computational optimisation to be applied in order to derive “optimal” solutions.

5.4.3 Results and discussion

A total of 331 supply and 9 demand scenarios (i.e. a total of 2,979 possible scenario combinations) were modelled with the adaptation strategies, leading to the identification of Pareto optimal sets for both decision making methods (RO and IG), trading-off the robustness of water supply and the PV of total cost (see Figure 5.10).

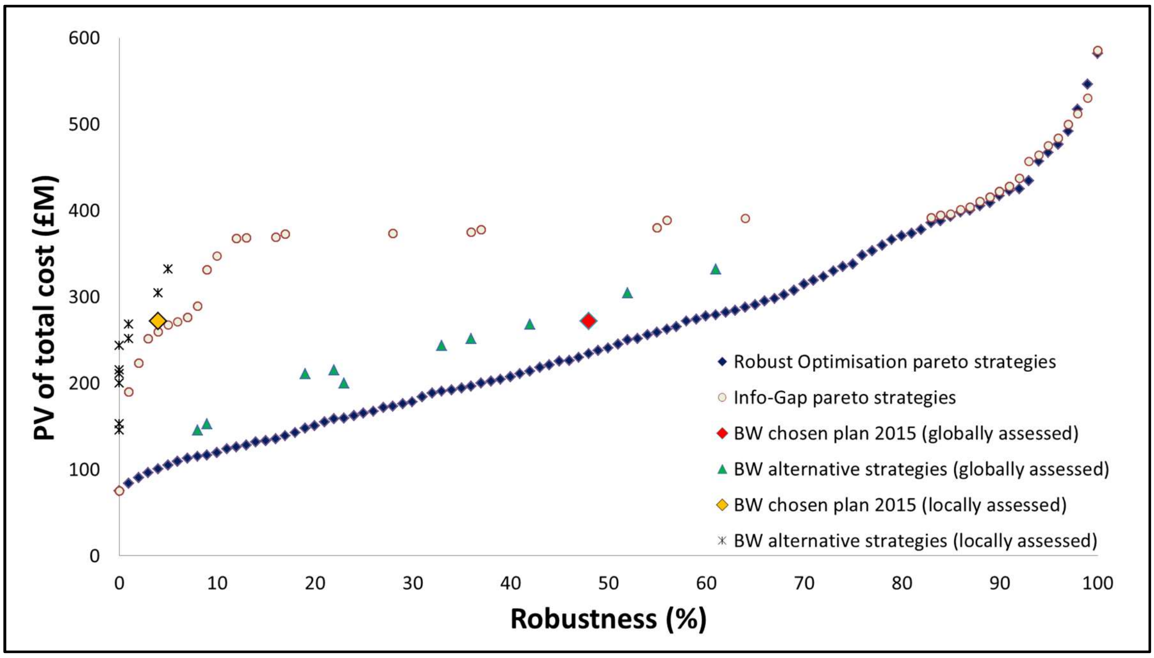

Figure 5.10: Pareto sets identified by the info-gap (U_{mid}) and robust optimisation methods – including the cost and robustness of BW's chosen plan 2015 and ten alternative strategies considered by BW examined by the IG local and RO global robustness models

As it can be seen from Figure 5.10, when compared to RO, the IG method produces higher-cost Pareto strategies for nearly all robustness levels. Although, both methods produce similar Pareto strategy solutions for plans providing >80% robustness, marked at the point at which the differences between the local and global robustness analysis are becoming negligible. The distribution of Pareto strategies across the range of robustness is also lower for the IG analysis. The reason for both occurrences is again due to IG's local robustness analysis leading to the more stringent localised performance requirements over the expanse of uncertainty, as fully discussed in section 5.3.3.

Bristol Water's preferred chosen plan for 2015 (Bristol Water, 2014), when examined in the RO global robustness model, delivered approximately 48%

robustness to uncertainty (Figure 5.10). This was somewhat to be expected as BW currently optimises to the median projections of supply and demand and using the 90% risk and uncertainty headroom additions. This translates to the median projections of supply and demand utilised in this investigation. Both BW's chosen plan and the alternative strategies they considered provided between 8-61% robustness when tested in the RO global model. This is due to the expanded level of uncertainty now being examined, as BW examined various alternative strategies with reduced or increased total costs, but still centred around an examination of the median projections of supply and demand.

However, the RO model identified numerous lower cost strategies for the same levels of robustness exhibited by the BW strategies and also provides a greater trade-off examination by identifying a wide range of Pareto optimal solutions. When examined in the IG robustness mapping model (see section 4.5.1), the BW strategies all exhibited significantly reduced robustness (all <6%). This further highlights the greatly increased constraints imposed by the localised mapping method of IG (discussed in section 5.3.3). Each BW alternative strategy is first assessed to the 'most likely' scenario combination ($\tilde{u}$), chosen as the median severity ranked supply and demand scenarios (see section 4.5.1), then must satisfy adjacently ranked scenarios sequentially. This highlights the issues of optimising plans to a single linear future pathway, as the selected strategies can prove weak to alternative future scenarios in close proximity to the initial 'most likely' projections.

This issue could be alleviated by switching to using increasing uncertainty variables; however, the purpose here was to examine how the DMMs handle complex 'scenario' assessments in practice, because approaches that focus on scenario development/assessment are increasingly considered for evaluating WRM adaptation strategies and the validity of management decisions to deep uncertainties (European Environment Agency, 2009; Lempert et al., 2003; Maier et al., 2016; Notten et al., 2003).

The trade-off with the IG method is that the Pareto strategy solutions, although having a greater PV of total cost for the same robustness level, will create systems that provide a greater system capacity increase by favouring larger infrastructure that will cover a wider set of variations in future scenario projections, as shown in Figure 5.11. IG typically favours strategies with higher DO resources in order to satisfy a wide range of scenarios in the expanding local robustness "search". It therefore doesn't favour the selection of small interventions because these don't provide additional robustness in the IG search (see Figures 5.11 and 5.12). These larger resource strategies then inherently have a higher associated cost. In short, IG encourages higher cost strategies and is unable to select lower cost/resource options.

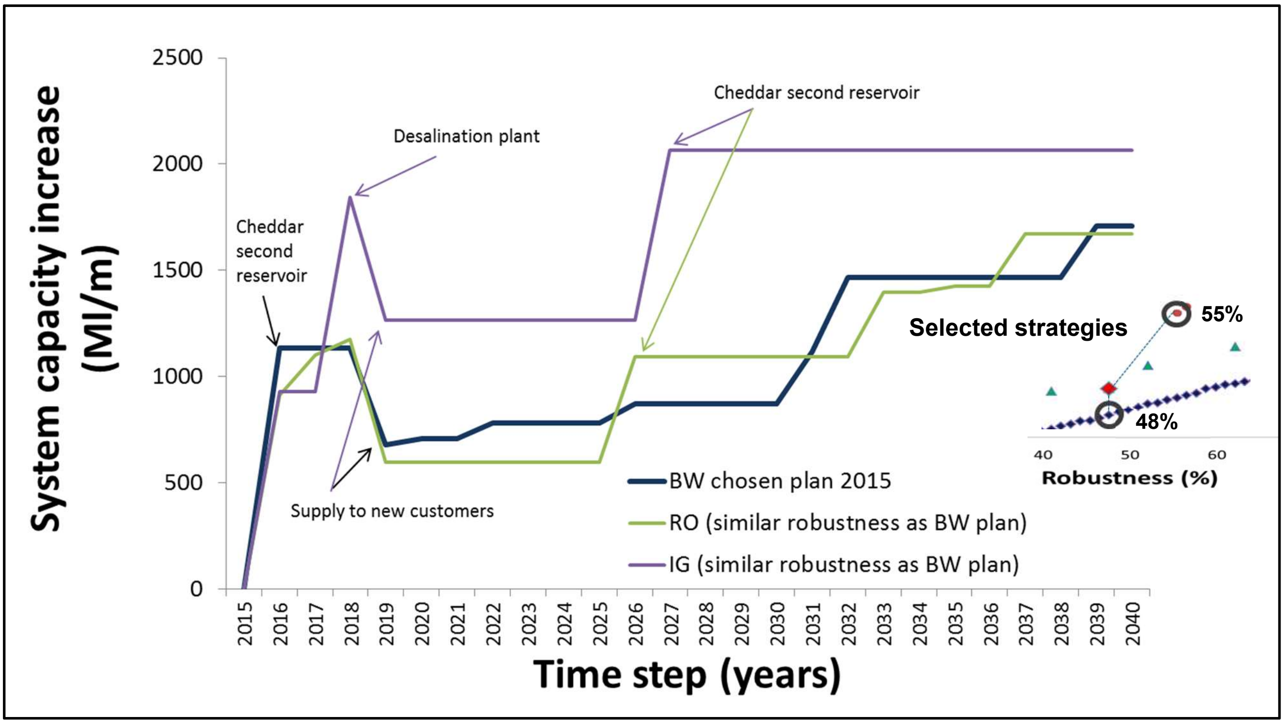

Figure 5.11: System capacity increases (water supply added to system) for the BW chosen plan 2015 and selected RO and IG strategies of similar robustness

Figure 5.11 shows the system capacity increase (water supply added to the BW system – in ML/month) over time by the BW chosen plan (Bristol Water, 2014) and by two adaptation strategies identified by the RO and IG methods with the most similar robustness to the BW chosen plan (as indicated in Figure 5.11). The reduction in supply for all strategies at 2018 is due to an additional output of 19 ML/d (578 ML/m) to new customers (see section 5.4.2.1). The RO strategy presents a very similar pattern of interventions to that of the BW chosen plan although cost savings are made by delaying the construction of the second reservoir at Cheddar (R4 – in Table 5.7) until 2025 and implementing more low-cost interventions in the initial time steps. The IG strategy differs from the RO and BW chosen plan by selecting fewer but larger interventions at key detected periods of the planning horizon, including a desalination plant (R3 – in Table 5.7) at 2017 to accommodate for the outgoing supply in 2018, and additional supply resources around 2025 to cater for the large shortfall in supply and rise in demand projected for this period onwards. This again highlights how IG typically favours strategies with higher DO resources in order to satisfy a wide range of scenarios in the expanding local robustness "search".

The full list of selected interventions for the strategies in Figure 5.11 is shown in Figure 5.12. It shows the optimised increase in smaller intervention options (cost and DO) selected by the RO solution (including several options not considered by the BW chosen plan) and the increase in larger scale but fewer options selected by the IG solution, again supporting the above conclusion.

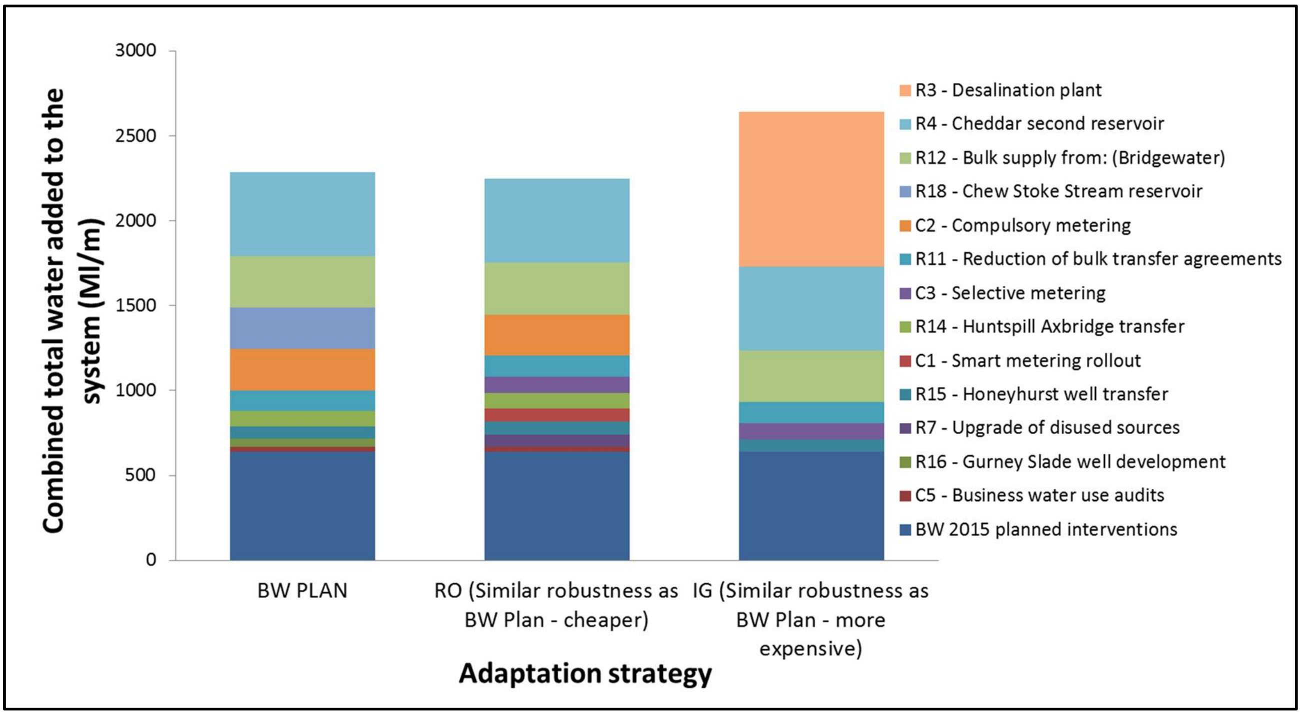

Figure 5.12: Intervention options proposed by the BW chosen plan 2015 and by selected RO and IG strategies of similar robustness

The RO Pareto strategy that has the same PV of total cost as the BW chosen plan 2015 (indicated in Figure 5.13) has an increased robustness of 58% when compared to the BW chosen plan. This strategy along with the 90% and 95% RO Pareto strategies (near identical to the IG Pareto strategies of the same robustness) are selected for further analysis (Figure 5.13). The strategy of similar PV of total cost but higher robustness (58%) then the BW plan (48%) reduced costs by delaying the second reservoir at Cheddar (R4) by two years and incorporating additional options to reduce water consumption early on in the planning horizon (options C1, C3 and C5) before implementing various minor additional sources and enforcing compulsory metering later in the planning horizon (options C2, R7 and R12). The additional system capacity added around 2018 by the RO's 58% robust strategy means few additional interventions were required over the 2019-2029 period, where conversely the BW plan imposed numerous water transfer schemes (R11, R14, R15) over this period to ensure supply levels remained just above the, very specific, target headroom level projected for this period. This led to a sequence of interventions of similar total cost, but less overall robustness than the strategy derived by RO. RO was able to derive this more robust strategy as it was directly optimising for robustness across the range of supply and demand scenario combinations. The conventional EBSD approach optimises to a single linear projected future (target headroom level) so the optimal sequence of interventions obtained is not as robust in handling deviations outside of the most likely set of conditions.

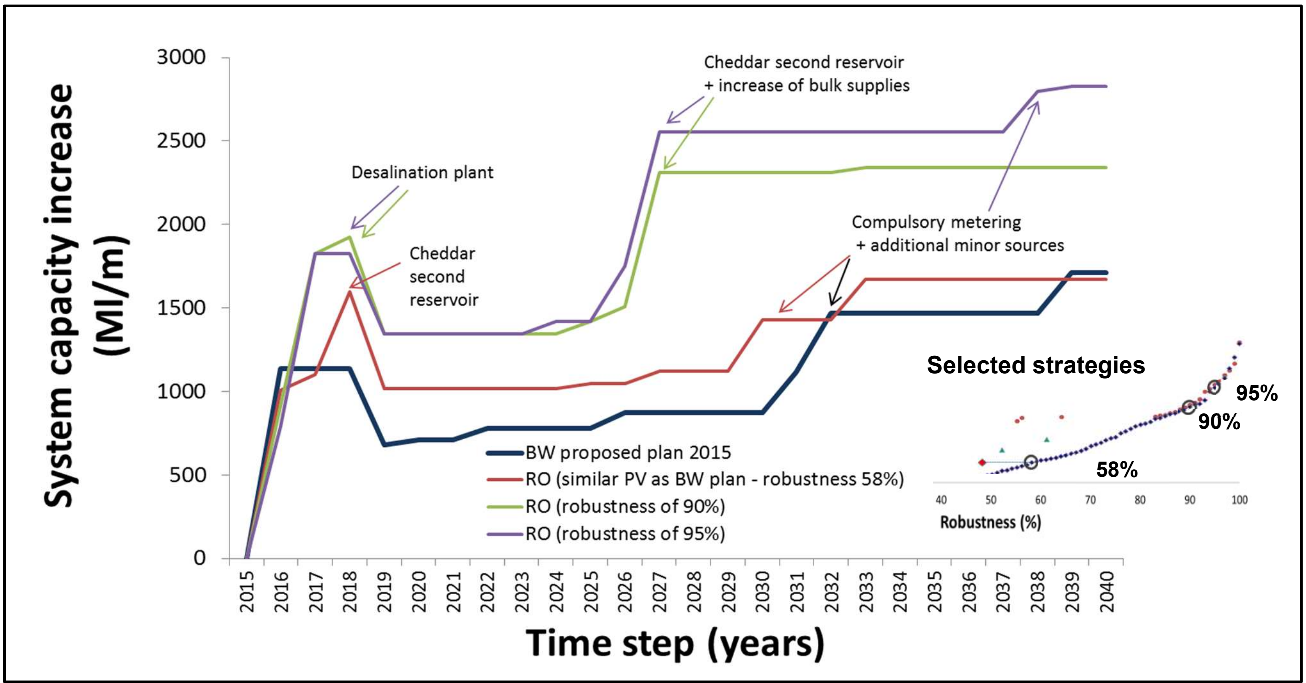

Figure 5.13: System capacity increases (water supply added to system) for the BW chosen plan and selected RO and IG strategies of higher robustness

If planning for a maximisation of robustness (solutions of 90% and 95% robustness in Figure 5.13) then both the RO and IG Pareto strategies recommend construction of a larger resource (e.g. the desalination plant (R3)) early in the planning horizon, followed by the second reservoir at Cheddar (R4) and various additional bulk supply / transfer options (R11, R12 and R14) at around 2025. This greatly increases system robustness to uncertainty but for an additional spending of £144-£195 million over 25 years on top of the current BW planned total expenditure of approximately £271 million. This would likely be deemed an overdesign given the BW's current planned expenditure, but what both DMMs allow is a comparison of Pareto optimal strategies across a wide range of robustness levels. This allows decision makers to then select an optimal trade-off solution, identifying an ideal robust adaptation strategy from a group within a desired range of expenditure.

Figure 5.14 presents the Pareto results derived from altering the initial starting location of the IG analysis (denoted as U_{high}, U_{mid} and U_{low}) – see section 4.5.1. From this investigation an increased variation between the Pareto strategies identified is exhibited compared to that of the Sussex North investigation.

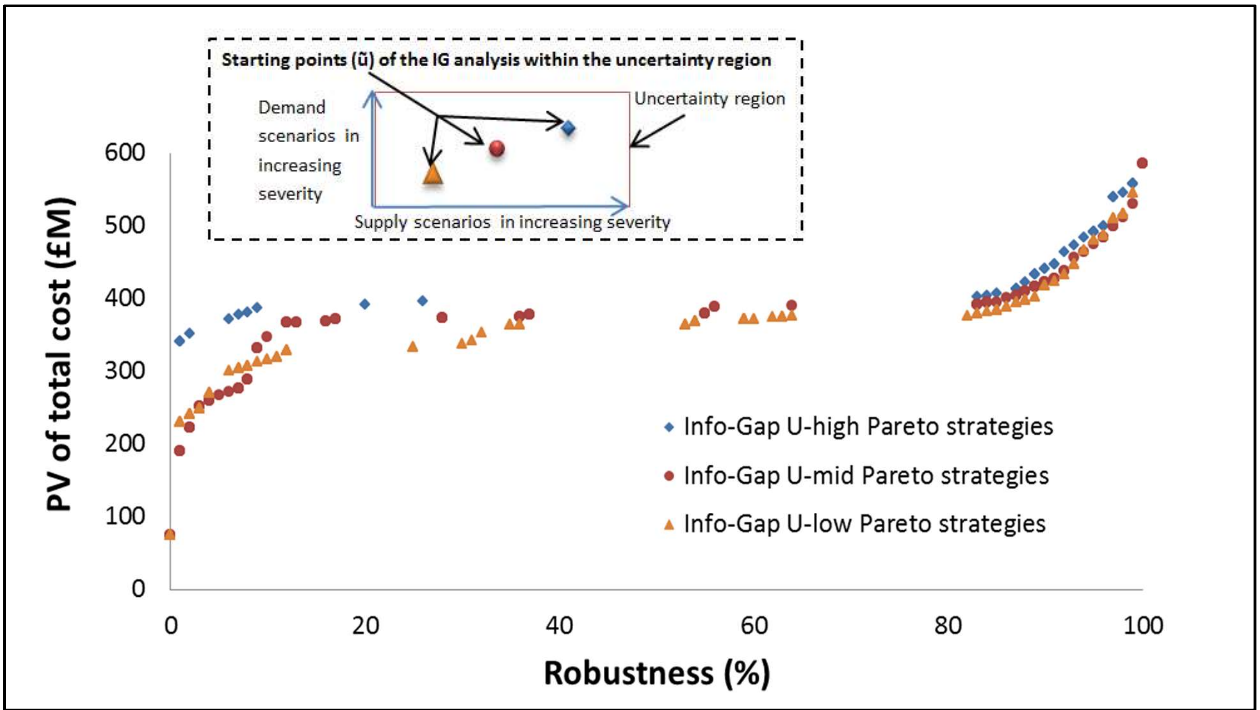

Figure 5.14: Pareto strategies identified by Info-Gap following variation of the initial start point of the analysis (denoted as U_{high}, U_{mid} and U_{low})

The added complexity in this case study, incorporating a wider region of uncertainty, has led to a greater variation in the adaptation strategies identified for different levels of robustness across the three examinations (U_{high}, U_{mid} and U_{low}); except at 100% robustness where all Pareto fronts converge on the same solution. The least variation can again be seen in the strategies of higher robustness (i.e. for robustness > 80%). These strategies can satisfy multiple scenario combinations across the range of uncertainty regardless of their starting location. Strategies of mid to low levels of robustness will generally be detected at a lower cost from the less severe starting points in the scenario rankings (the triangles and circles in Figure 5.14), as more easily satisfied scenarios (of supply and demand) will be in closer proximity to these starting locations. This clarifies that the starting point becomes more important the larger the uncertainty region becomes and so should be selected with great care.

The final analysis involves an investigation into the effect of altering the length of the planning horizon. The current 25 year planning horizon (2015-2039 inclusive) is compared with an extended 50 year planning horizon (2015-2064 inclusive). Both methodologies are re-tested, as described in Chapter 4, using the extended time steps from the 50 year planning horizon and new Pareto strategies are identified (Figure 5.15 (a)). The two Pareto fronts follow a similar pattern to the fronts shown in Figure 5.10, with both fronts near converging around 75-80% robustness; however, the IG Pareto front now contains a larger number of solutions following the 50 year planning horizon runs, as a greater variation of intervention sequences are now available.

In order to examine whether the extended 50 year planning horizon has affected the timing and scale of intervention options sequenced over the first 25 years the IG and RO Pareto strategies of 90% and 95% robustness derived using a 50 year planning horizon (circled in Figure 5.15 (a)), are compared with the corresponding RO strategies of 90% and 95% robustness derived using a 25 year planning horizon (shown in Figure 5.13). These comparisons are shown in Figure 5.15 (b) and (c) respectively.

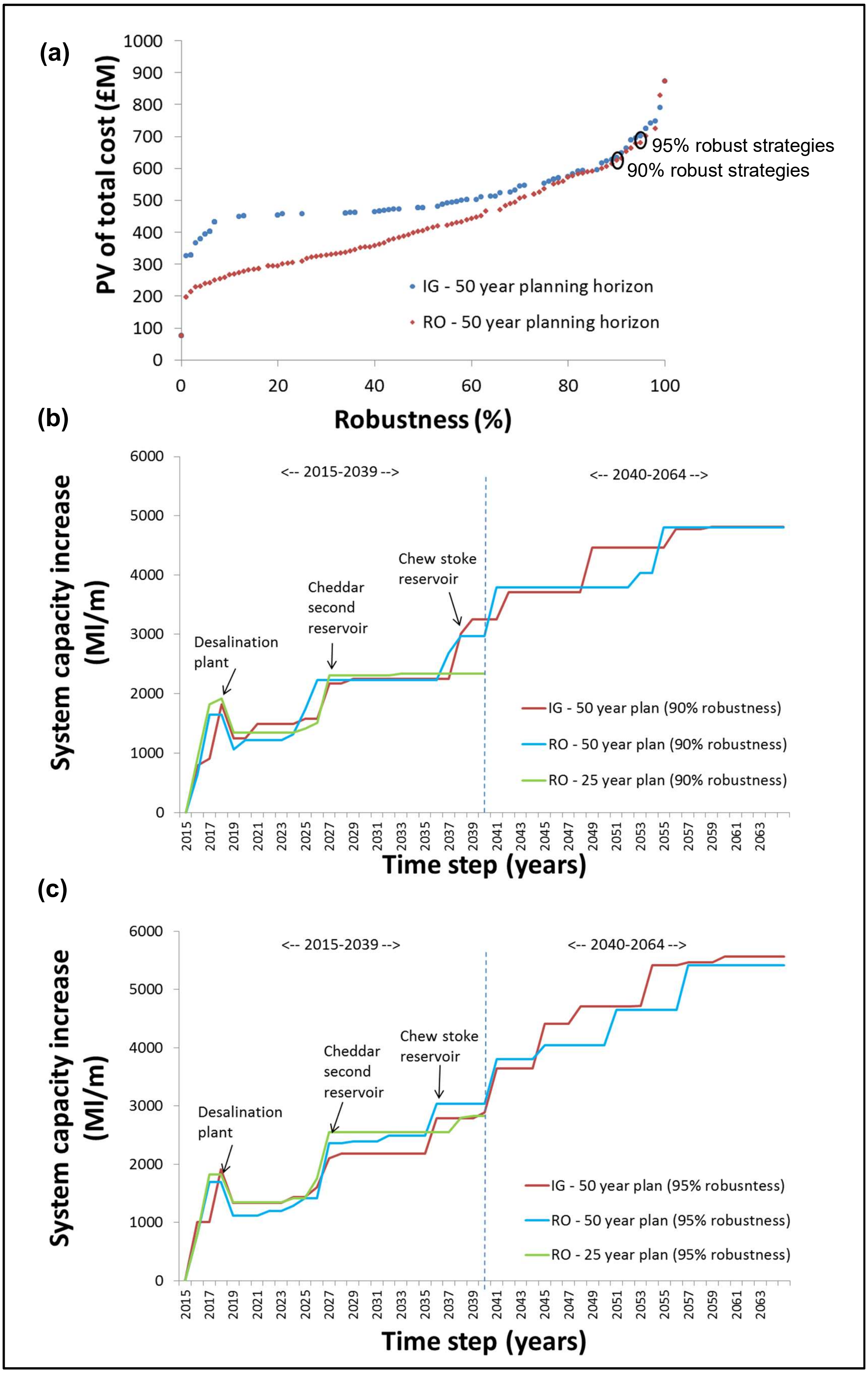

Figure 5.15: (a) Pareto strategies identified by IG (U_{mid}) and RO methods when utilising a 50 year planning horizon; (b) system capacity increases for 90% robust strategies identified over 50 and 25 year planning horizons; (c) system capacity increases for 95% robust strategies identified over 50 and 25 year planning horizons

The strategies compared present a fairly similar sequence of intervention options selected over the initial 25 years. All three strategies recommend construction of a larger water resource (e.g. the desalination plant - R3) two or three years into the planning horizon, followed by a second larger resource (e.g. the second Cheddar reservoir (R4)) after 2025. The main difference comes in the timing of intervention options and in the additional construction of large resource (either Chew Stoke reservoir (R18), or a new bulk supply from Severn Springs (R10) or Vyrnwy (R13)) at around 2035-2038 years into the planning horizon for the adaptation strategies examined over 50 year horizons. This is due to the strategies preparing for future climate change impacts projected post 2040, which is not examined in the 25 year planning procedures. However, the current industry standard 25 year WRMPs are re-evaluated every 5 years, so additional resources required later in the planning horizon may be identified and included over time should they be required.

An advantage of planning further into the future means a more robust plan can be developed for the near term whilst ensuring a least-cost robust plan is constantly refined over the long term. However, at least in the case study analysed here, extending the planning horizon by 25 years does not significantly alter the optimal plans identified over the preliminary 25 year period. Similar intervention options are selected; however, the timing of those options shows a slight variation.

5.4.4 Conclusions

This case study provided a comparison of two DMMs for integrated water resource management under deep uncertainty. The Robust Optimisation and Info-Gap methods were applied and compared on the case study of the Bristol Water resource zone in the UK with the aim to solve a specific WRM problem driven by the maximisation of robustness of long-term water supply and minimisation of associated costs of adaptation strategies, all under a range of uncertain future supply/demand scenarios. The results obtained lead to the following key conclusions:

1. Optimisation based automatic generation of strategies was required for the IG method in order to test a suitable range of strategy formulations

given the larger data sets and a larger pool of potential intervention options applied in this more complex case study.

2. The two DMMs analysed produced different Pareto adaptation strategy recommendations to each other and to the strategies derived using the current UK engineering practice. Robust Optimisation generally produced lower costing Pareto strategies than IG for all ranges of desired system robustness due to RO’s less stringent method of global analysis. Info-Gap’s local analysis generally lead to larger scale interventions selected earlier in the planning horizon in order to satisfy the widening range of variable scenarios.
3. The location of the starting points of the IG analysis altered the Pareto strategy results obtained across all robustness levels and examinations (U_{high}, U_{mid} and U_{low}), especially at lower robustness levels. This was due to the increased case study complexity utilising a larger region of uncertainty and highlighted the importance of carefully selecting the initial start point.
4. Varying the length of the planning horizon from 25 to 50 years did not significantly alter the optimal plans identified over the preliminary 25 year period. Similar intervention options are selected; however the timing of those options showed a slight variation.
5. The variation in the Pareto strategies derived highlight how the current industry standard for water supply system adaptation planning could benefit by applying a wider range of decision methodologies and assessment tools (especially those that explicitly quantify a level of system “robustness”) as well as a more encompassing investigation into potential future uncertainties and alternative *prospective* methods for scenario generation.

5.5 Summary

Two real-world quantitative case studies were carried out to analyse the performance and suitability of decision making methods Robust Optimisation and Info-Gap decision theory in application to water resource management adaptation problems under deep uncertainty. The two methods were applied and compared on case studies of Southern Water's Sussex North resource zone and the Bristol Water resource zone, both situated in the UK. The methods aimed to solve a specific water resource management problem driven by the maximisation of robustness of long-term water supply and minimisation of associated costs of adaptation strategies, all under a range of uncertain future supply/demand scenarios. The case studies were of varying complexity and utilised alternative performance indicators, planning horizons and scales of uncertainty. The primary investigation was into: (a) a local vs global method of robustness analysis and (b) utilising pre-specified vs optimisation-generated adaptation strategies, but also incorporated: a study of utilising Future Flow climate/hydrology projections to produce *prospective* supply and demand scenarios and a comparison with current UK engineering practice. The specific results and conclusions for the Sussex North and Bristol Water case studies are detailed in section 5.3.4 and 5.4.4 respectively. The overall key WRM conclusions derived across the two case studies are as follows:

1. The two DMMs examined allowed a comparison of local vs global measures of robustness (investigative area (a) from section 3.5). Robust Optimisation, with its global robustness analysis, appears the more favourable DMM for the WRM problems examined here. Its simpler computational set-up and operation allowed an easier examination of future scenarios when utilising an ensemble of *prospective* transient flow projections. The RO analysis also led to the identification of lower costing adaptation strategies across both case studies for all given levels of desired robustness. Info-Gap had a more complex set-up and the localised mapping methodology proved problematic when applied to a wide range of discrete scenario projections that were extremely variable and not monotonically increasing.
2. The novel area-based robustness search technique developed for the IG method application improved on previous scenario mapping practices by allowing more scenario combinations to be analysed and allowing the robustness search to continue until all scenario expansion routes ended in system failure.
3. The location of the starting points of the IG analysis did not significantly alter the Pareto strategy results obtained in the simpler case study

(Sussex North) but did in the more complex problem (Bristol Water). The Bristol water study utilised a larger region of uncertainty signifying that the starting location of the IG analysis is more impacting on outputs as the uncertainty region increases, highlighting the importance of carefully selecting the initial start point.

4. The IG performance could be improved by switching to using uncertainty variables instead of using transient flow projections; however, the purpose here was to examine how the DMMs handle complex ‘scenario’ assessments in practice, as approaches that characterise uncertainty via scenario development/assessment are being increasingly regarded as the next step for evaluating complex systems to deep uncertainties (Maier et al., 2016; Moss et al., 2010).
5. In assessment of pre-specified vs optimisation-generated adaptation strategies (investigative area (b) from section 3.5), it was discovered that Info-Gap required optimisation based automatic generation of strategies as the case studies became more complex. The larger pool of potential intervention options made it problematic to reliably pre-specify strategies for testing, reinforcing the suitability of a form of Robust Optimisation for WRM adaptation planning.
6. A comparison of singular vs Pareto optimal results was also examined (investigative area (f) from section 3.5). Both DMMs could produce a Pareto optimal set of adaptation strategies (either formed automatically or following the ranking of results), which ultimately allows a visualisation of trade-offs across the objectives before final strategy selection is carried out. This improves on current UK engineering practice, which typically pre-specifies a linear projection of future supply and demand and then optimises to derive a single optimal adaptation strategy solution. Single objective (least cost) optimisation, as in the current practice EBSD method, effectively determines only a single point on the Pareto fronts identified by the DMMs here, and so does not provide any trade-off comparisons.
7. The two DMMs examined also facilitated an examination of a “fixed” vs “fixed-adaptive” strategy design (investigative area (d) from section 3.5). A fixed strategy design (i.e. unchanging the set sequence of interventions in

the strategies examined from input to output) suffers from the same computational issues experienced when pre-specifying a selection of strategies when system complexity, larger data sets and a larger pool of potential intervention options are used. A fixed-adaptive design (either manually altering strategy designs as vulnerabilities are detected (as with RDM), or mutating strategy designs within optimisation processes (as done here with RO)) proves more beneficial at testing multiple strategy design configurations in a much more computational acceptable time frame. Examining every form of potential fixed strategy design when millions of potential combinations exist is not practical.

8. The comparison between using a risk-based metric and an individual criterion (reliability) based metric (investigative area (g) in section 3.5) is difficult to directly analyse across the two case studies; although, from an immediate practical point of view it is arguably more informative to use a reliability criterion to measure the performance of the water system as it provides clearer insight into the relative frequency of water deficits detected over the planning horizon. The risk-based metric identified strategies that could maintain a given level of risk over a given planning horizon; however, the calculation of risk is far less transparent when you amalgamate both likelihood and severity into a single parameter and it remains unclear just *how many* water deficits are occurring and at *what magnitude*. In order to better compare the effect of altering the performance metrics utilised it is recommended that a more complete investigation into potential indicators be conducted, which explore individual criterions of performance; such as examining the frequency, duration and magnitude of water deficits (Hashimoto et al, 1982) and how this can better inform decision makers on the performance of the water system.

9. In comparison with the SW and BW WRMPs 2015-40 proposed plans it can be concluded that quantifying the robustness explicitly (as opposed to indirectly, via headroom and level of service failure) and using this and costs as drivers to identify solutions, is likely to result in more robust and less costly plans when compared to a more conventional approach used in current UK engineering practice. However it was observed, at least in

the case studies analysed here, that increasing the current 25 year planning horizon to a 50 year analysis did not significantly influence the intervention options selected over the initial 25 years of the plan.

The differences in DMM outputs highlight how the current industry standard for water supply system adaptation planning could benefit by applying a wider range of decision methodologies and assessment tools as well as a more encompassing investigation into potential future uncertainties. The requirement to apply optimisation to the IG method suggests that the development of an optimal DM framework for complex WRM planning under uncertainty may involve one that will utilise (perhaps hybridise) features from a range of DMMs with the aim to exploit advantages and minimise disadvantages of existing methods (e.g., using optimisation to select and test more strategy combinations, combined with new vulnerability map or scenario discovery methodologies (e.g., Singh et al., 2014)) with objectives set up to examine the trade-offs between robust and flexible solutions across multiple objectives.

The flexibility of solutions is another aspect not explored within the approaches presented here. In practice, evaluating only fixed rather than flexible-adaptive strategies limits the range of potential long-term trade-offs explored. This limitation could be overcome by combining the DMMs tested here with modern approaches such as real options analysis (Jeuland and Whittington, 2014), adaptive pathways (Kwakkel et al., 2015), or adaptive multi-objective optimal sequencing (Beh et al., 2015a).

In addition to the above mentioned conclusions two alternative performance metrics were also applied to the two case studies, but no significant conclusions could be derived as to their impact on strategy selection. In order to perform a more quantitative comparison of potential performance metrics it was recommended that a more in-depth analysis of the various indicators of water system performance be carried out. This investigation now follows in Chapter 6.

Chapter 6. Resilience-Based Performance Assessment for WRM Under Uncertainty

6.1 Introduction

Multiple methods exist for assessing WRM systems under deep uncertainty; however, the output results from adaptation investigations can be highly dependent on the performance metrics employed.

A performance metric (or criterion) defines the performance of a water system to a single future scenario or set of conditions. The more well-known performance criterions often cited within WRM literature (as detailed in section 2.5.7) are those of Hashimoto et al. (1982) who were among the first to propose the use of the terms; reliability, vulnerability and resilience for water resource system performance evaluation. These performance criteria, in general, refer to how likely a system is to fail (its reliability), how severe the consequences of failure might be (its vulnerability) and how quickly it can bounce back, which is the recovery from a failure (its resilience).

In current UK engineering practice the EBSD 'levels of service' method most commonly assess the performance of a water system as the likelihood of temporary customer demand restrictions being enforced. This is a metric most closely related to that of 'reliability'. The 'vulnerability' of the system is also implicitly included in the control rules and triggers used to define each 'level of service' event for a given resource system, however current practice does not explicitly consider the 'resilience' of the system. The latest investigation by the EA into water resource planning methods of the future (Environment Agency, 2013a), called for a review of the EBSD 'levels of service' method and for the advancement of incorporating more resilience into water resource system planning, indicating it will support adaptation strategies that are aimed at improving system resilience. However a clear definition of resilience was not given in this report and resilience, to date, currently lacks a precise definition for practical real world water resource system performance evaluation.

In the previous chapter, two alternative performance metrics (reliability and risk-based metrics) were applied to the two independent case studies; however, no significant conclusions could be derived as to their direct impact on adaptation strategy selection. In order to further explore and analyse a range of applicable metrics a more detailed investigation is conducted. This chapter explores alternative assessment metrics addressing different aspects of a water supply system's resilience to uncertain climate change, i.e. to uncertain future supply and demand over a pre-specified long-term time horizon. The sensitivity and correlation between the various metrics is examined and the 'most suitable' metric that could characterise water system *resilience* is selected for a follow on investigation (Chapter 7). The metric chosen is employed in a newly developed resilience driven methodology; to compare the derived strategy solutions to that of current engineering practice solutions and to ascertain the metrics potential as an answer to the water industries need to define and include more emphasis on *resilience* in future water resource design and adaptation planning (Charlton and Arnell, 2011; Environment Agency, 2013a).

First the selected performance metrics are listed and described, followed by a description of the methodology applied to explore the metrics. An analysis of the metrics then follows, including an examination of metric sensitivity and correlation, and a more in-depth examination of the behaviour of water deficit periods, before a recommendation is made of a most appropriate metric to characterise system resilience. The selected metric is then applied to a novel resilience-based methodology for WRM adaptation planning (Chapter 7).

6.2 Methodology

6.2.1 Objective, problem definition and main procedure

The objective of this examination is to select, analyse and compare a range of different metrics (or criterions) that could be used to assess and indicate the performance of a water system to a given future scenario of supply and demand. The ultimate goal is to identify and further examine a single individual metric that has the potential to be the defining metric and calculation of the term 'resilience' of a water system. The task included 6 main procedural steps as outlined below:

1. Identified a group of potential metrics to quantify the resilience-based performance of a water resource management system.
2. Selected a suitable real-world case study, utilising a dynamic long-term supply/demand balance water resource simulation model.
3. Generate a range of plausible future supply and demand scenarios to examine the varying effect they have on the metric results.
4. Identified a group of realistic adaptation strategies to apply to the case study to further examine the effect they have on the performance metric results.
5. Perform a number of simulation model runs based on the above and calculate performance metrics values and related results.
6. Analyse results to identify the most promising/suitable metric(s) for further investigation as a metric of resilience.

6.2.2 Metrics under assessment

In order to select a range of metrics for analysis first a set of desirable metric characteristics are explored, derived by reviewing a range of WRM documents and reports (Defra, 2011b, 2013, 2016a, Environment Agency, 2013a, 2015; UKWIR, 2016a). Some characteristics of a good metric in the context of WRM are listed in Table 6.1 (in reference to the resilience of a water supply system; in no particular order):

Table 6.1: Characteristics of a good performance metric for WRM adaptation planning

Item	Description	Rationale
1	Practical	Quantitative rather than qualitative.
2	Comprehensive	Covers all important aspects of system resilience (how well is the system prepared to, affected by, responds to and recovers from a deficit event), including attributes of deficit events (frequency, time/duration and magnitude).
3	Understandable/ transparent	Easy to understand, and explain to, different, non-technical stakeholders.

Item	Description	Rationale
4	Non-redundant	A set of independent and specific metrics.
5	Minimal	As small as possible number of resilience metrics adopted eventually.
6	Defensible	Enables calculation of and comparison to relevant conventional measures in the context (reliability, risk / likelihood / impact, etc.).
7	Industry focused	Enables water industry to express its current goals and objectives.
8	Strategic	Embodies a strategic objective and can provide sufficient information to correctly monitor, plan and adapt a water supply system.
9	Accurate	Can be accurately projected/calculated for a given system, free of approximates and indistinct values.
10	Sensitive	The metrics need to provide a clear indication of improvement or deterioration.
11	Standardised	Deriving a metric definition that all respective parties can agree on that can be easily examined/calculated and understood by all relevant companies/organisations/individuals.
12	Informative	The metrics need to provide useful information that a decision maker can accurately utilise to quantify the relevant social, environmental and economic benefits/costs associated to the performance of a system.

Ten potential metrics to characterise different aspects of water system resilience have been selected for this assessment. To be compatible with current UK engineering practice the metrics chosen all relate to aspects surrounding threshold levels and trigger points of low water resource periods, i.e. water deficit events. The ten metrics are selected as they are deemed to cover all significant aspects of a water deficit event or water deficit *period*. A water deficit *event* was defined, in section 4.2.2.1, as the point at which a water system requires a temporary water restriction to be put in place (e.g. a temporary use ban) due to a critical threshold of low resource being surpassed. A water deficit *period* is here defined as the period of consecutive days/months the water system remains in deficit.

Figure 6.1 illustrates the ten potential resilience metrics derived for examination which aim to cover all aspects of individual water deficits *events* and prolonged water deficit *periods*. The ten metrics selected are as follows:

Duration based metrics

M1. Total time system is under water deficit (months)
M2. Duration of the longest water deficit period (months)
M3. Time to reach water deficit of greatest magnitude (months)
M4. Time to recover from water deficit of greatest magnitude (months)
M5. Average duration of water deficit periods (months)

Frequency based metrics

M6. Number of water deficit periods recorded (-)

Magnitude based metrics

M7. Water deficit of greatest magnitude recorded (Ml/month)
M8. Average magnitude of water deficits (Ml/month)
M9. Average magnitude of water deficit period peaks (Ml/month)

Volume based metrics – magnitude x duration

M10. Total volume of all water deficits recorded (Ml)

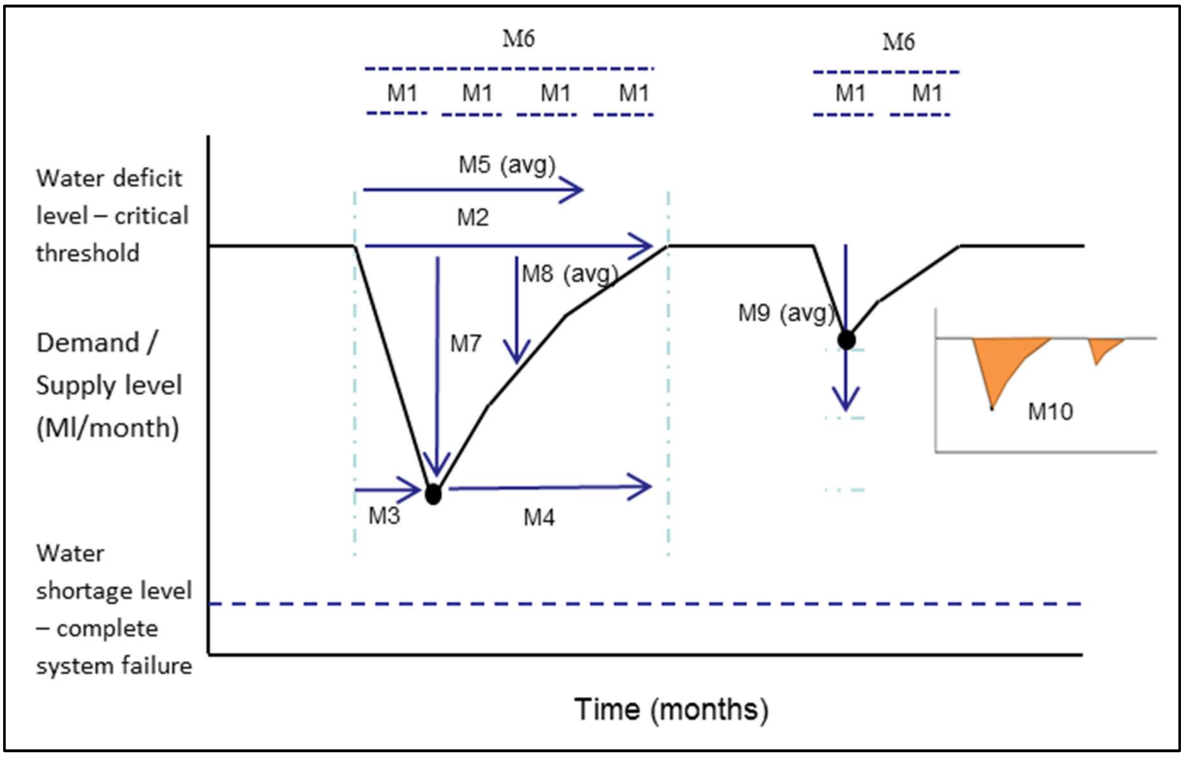

Figure 6.1: The ten performance/assessment metrics as calculated from a series of example water deficit periods

These ten metrics (Figure 6.1) were selected to cover the whole range of different assessment features of water deficit events/periods (i.e. duration, magnitude, frequency, etc.) and because they encapsulate many of the highlighted characteristics of what would make a good resilience-based performance metric for WRM adaptation planning (see Table 6.1). For instance, the metrics are all quantitative rather than qualitative (item (1) in Table 6.1); are transparent in their direct calculation (item (3)); are highly specific (i.e. do not encompass too many aspects into one calculation – item (4)); are industry focused (i.e. can be used to quantitatively express the industries qualitative goals – item (7)); can be used to directly monitor and adapt strategic plans (item (8)); can be calculated to an exact (non-approximated) figure during uncertainty/future scenario examinations (item (9)), and can be easily standardised (i.e. examined, understood and agreed upon by all relevant parties – item (11)).

The current classification of resilience within WRM practice in the UK is still very much a qualitative description rather than quantitative metric (Ofwat, 2015; UKWIR, 2016a; Water UK, 2016). The following assessment is carried out to examine several quantitative aspects of the metrics such as how sensitive, informative and comprehensive the candidate metrics are (items (2), (10) and (12) from Table 6.1) in order to identify a smaller number, ideally singular criterion, of resilience that is defensible against conventional practices (items (5) and (6)).

6.2.3 Assessment set-up

The dynamic water resource simulation model (as described in section 4.3) is set up for the Bristol Water case study (as described in section 5.4) and utilised to test the ten potential resilience metrics listed in section 6.2.2.

The Bristol Water case study included the generation of 331 discrete future supply scenarios and 9 future demand scenarios, which were subsequently ordered into a range of severity. The full range of scenarios are not used in this metric examination in order to allow a more considered examination with more detailed analysis of individual scenarios tested. The many thousand possible scenarios combinations available would also yield an unnecessarily vast range of individual results if all tested, which would be very computationally demanding due to the multiple simulation runs required. Therefore, in order to examine the sensitivity of the metrics across a range of uncertain future supply and demand scenarios a subset of scenarios (20 supply and 3 demand scenarios) of varying severity are selected at intervals from across the range of uncertainty. This produced a total of 60 future scenario combinations (of supply and demand) for assessment purposes that encompass projections of low to high demand and low to high changes in future supply availability, but ensuring that the more extreme projections are also included, to see how the system responds to being stressed beyond what it has been designed to.

Four intervention adaptation strategies were selected for the evaluation of metrics. These strategies entail a varying degree of system adaption and include a strategy of “no” adaptation (i.e. no interventions applied across the planning horizon) through to “low”, “moderate” and “high” level adaptation where multiple intervention options were applied across the planning horizon, as detailed in Table 6.2 (full intervention option information is detailed in Table 5.7).

Table 6.2: Adaptation strategies examined

Intervention option / year of implementation	No adaptation	Low adaptation	Moderate adaptation	High adaptation
OPTIONS TO REDUCE WATER LOSSES				
Pressure reduction (D1)	-	2015	2015	2015
Supply Pipe replacement (D4)	-	2025	2015	2015
Active Leakage Control (ALC) (D6)	-	2025	2015	2015
OPTIONS TO PROVIDE ADDITIONAL RESOURCES				
Reduction of bulk transfer agreements (R11)	-	-	2025	2015
Honeyhurst Well transfer to Cheddar (R15)	-	-	-	2020
Huntspill Axbridge transfer (R14)	-	-	-	2025
OPTIONS TO REDUCE WATER CONSUMPTION				
Selective metering of domestic customers (C3)	-	-	-	2025

The four adaptation strategies were applied to the Bristol Water existing system configuration and tested over the 60 future scenario combinations of supply and demand over a 25 year planning horizon. The resulting water deficits were then assessed in relation to each listed performance metric (M1-M10).

6.3 Resilience metrics analysis – sensitivity assessment

The performance metrics values are calculated for each adaptation strategy over each future scenario combination of supply and demand, resulting in 60 individual results for each performance metric and each strategy. Box plots are then produced for each set of metrics in order to gauge the sensitivity of each metric across the scenarios and across the increasing levels of adaptation applied to the system (see Figure 6.2).

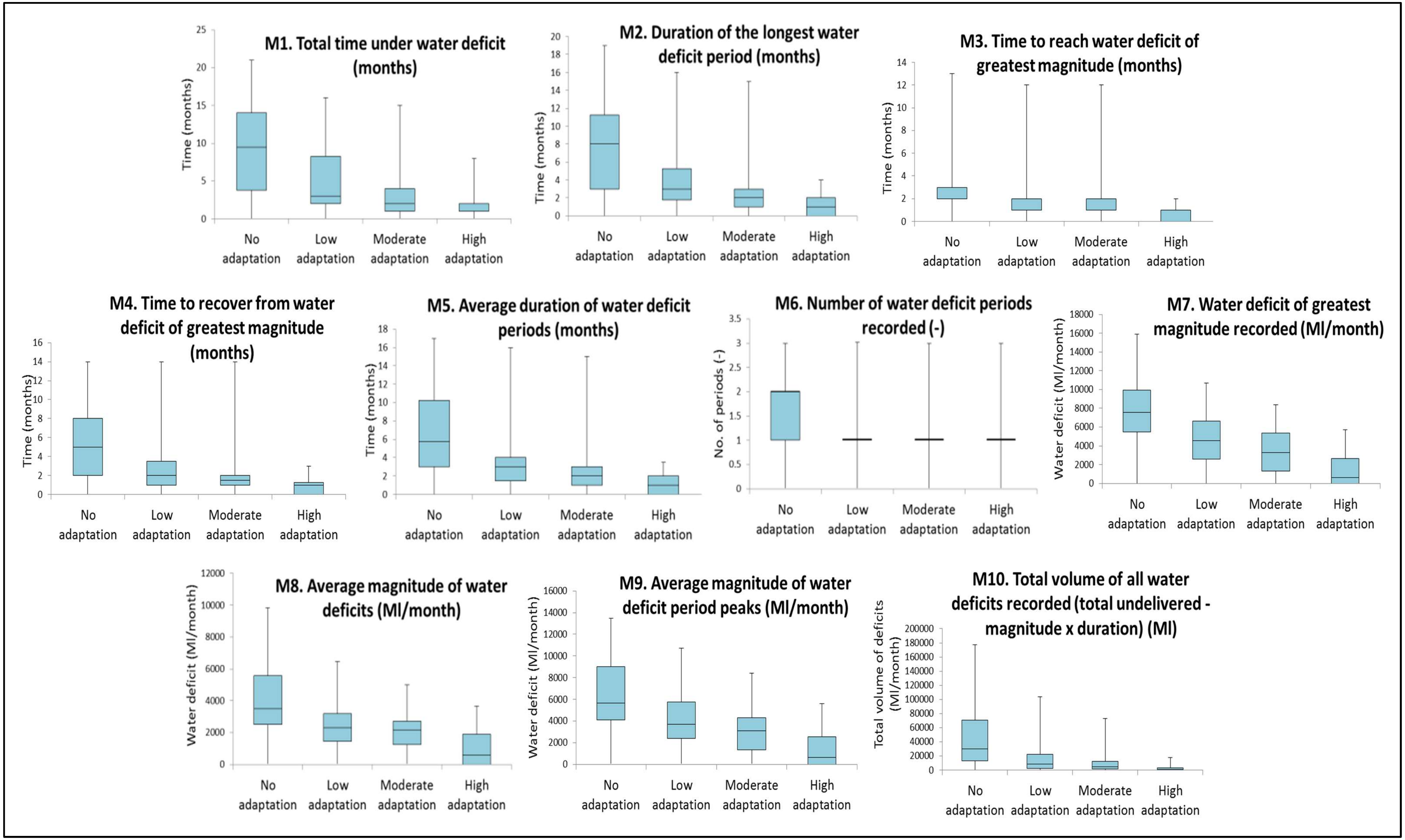

Figure 6.2: Box plots of performance metric results for all strategies across all scenarios

The following can be noted from Figure 6.2: (a) most metric media (trend) values reduce (i.e. improve) with increasing levels of adaptation but not always, as can be seen with metric M6, where the number (e.g. frequency) of water deficit periods detected from low to high adaptation exhibit the same median and min to max values. The increasing level of system adaptation reduces the duration and magnitude of the detected water deficit periods (as can be seen in the alternative metric box plots). This, however, highlights the misperception that can arise from using frequency only based metrics that do not make a more detailed assessment, i.e. take duration or absolute magnitude of deficits into account; (b) the variation (e.g. min to max and interquartile range) of most of metric values also reduces with increasing level of adaptation although again not necessarily always (e.g. M3 and M6). Therefore, utilising metrics M3 and M6 would likely only lead to the recommendation of a low level of adaptation, whereas applying the alternative metrics would lead to greater adaptation recommendations to increase overall system performance.

Metrics that are more sensitive to changing conditions are preferable to those that indicate little change in system performance (see Table 6.1), as sensitive metrics can provide a clear indication of system improvement or deterioration. To evaluate the relative sensitivity of each potential resilience metric, graphs are plotted which show the normalised sensitivity of each metric for each strategy for all scenarios (Figure 6.3). Each coloured line on Figure 6.3 represents one individual discrete future scenario of supply and demand and its respective (normalised) value for each metric. The scenario lines on Figure 6.3 illustrate how one given scenario can produce very different results when analysed to one metric rather than another.

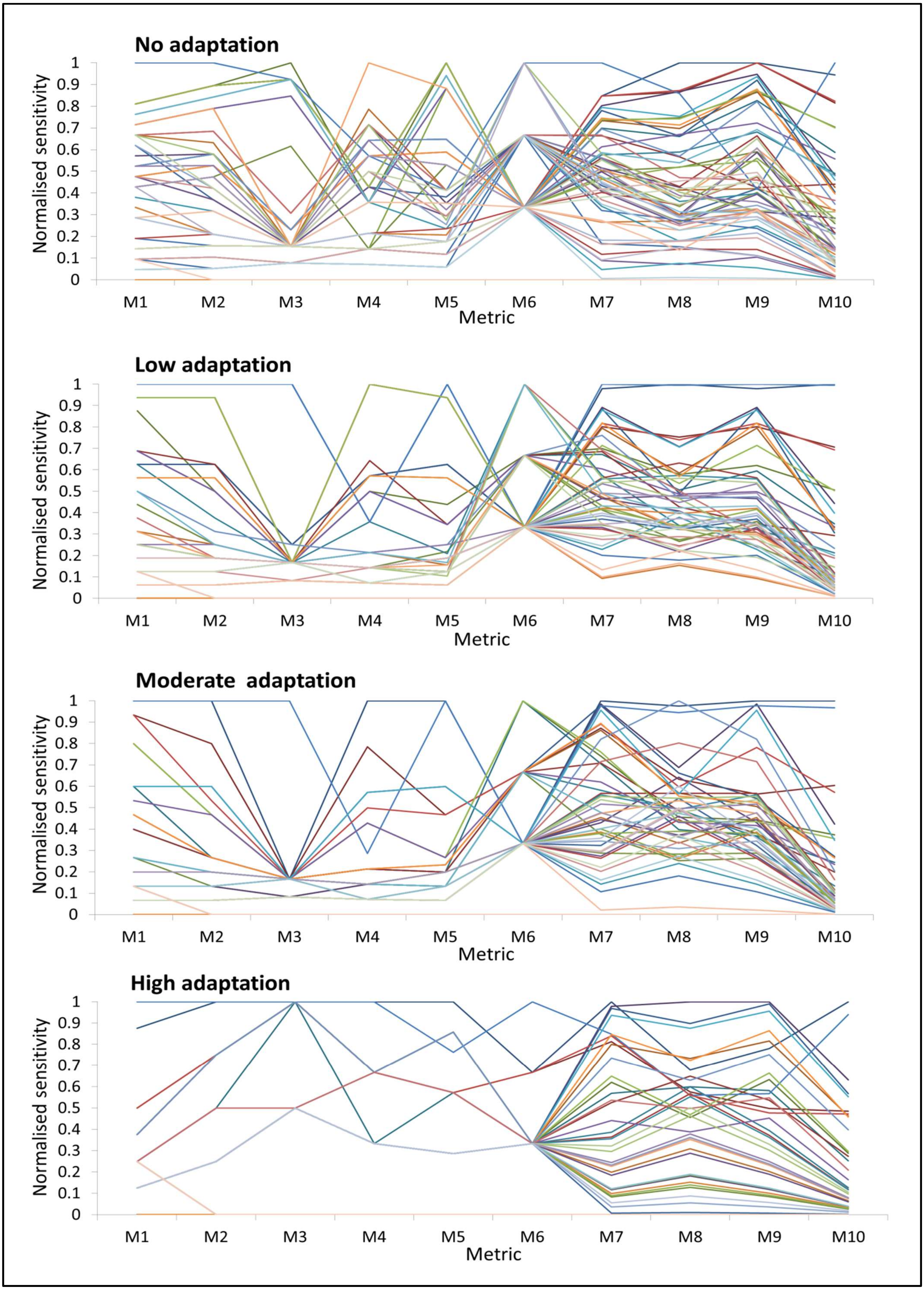

Figure 6.3: Normalised sensitivity of each metric across all scenarios

The results generally show the magnitude metrics (M7-M9) to be the most sensitive and maintain the greatest sensitivity across the increasing adaptations to the system, whilst time to water deficit of greatest magnitude (M3) and number of water deficit periods (M6) are the least sensitive. For the duration based metrics – total time under water deficit (M1) and the duration of the longest water deficit (M2) maintain the greater sensitivity across the scenarios. Metrics M3-M5 tend to 'clump' more often around isolated values for multiple scenarios making the difference in performance under each scenario, or from one strategy to another, harder to ascertain. The variation in recorded performance for the time to reach (M3) and recover from (M4) a water deficit of greatest magnitude also often tend to fluctuate (lines cross) from one scenario to the next. This presents a problem if utilising one of these metrics individually; as the time for the system to recover (M4) may be of low duration under a given scenario, leading a decision analyst to believe this strategy is performing well over this scenario; however, it may instead exhibit a long duration of time to reach the deficit of greatest magnitude (M3) and vice versa.

To investigate the low variation of the time to reach water deficit of greatest magnitude (M3) and the performance of the alternative metrics the largest deficit periods within a selection of scenarios are isolated and given a more detailed assessment. Three scenarios are selected from across the scenario severity range and the longest water deficit periods are examined in more detail, as shown in Figure 6.4.

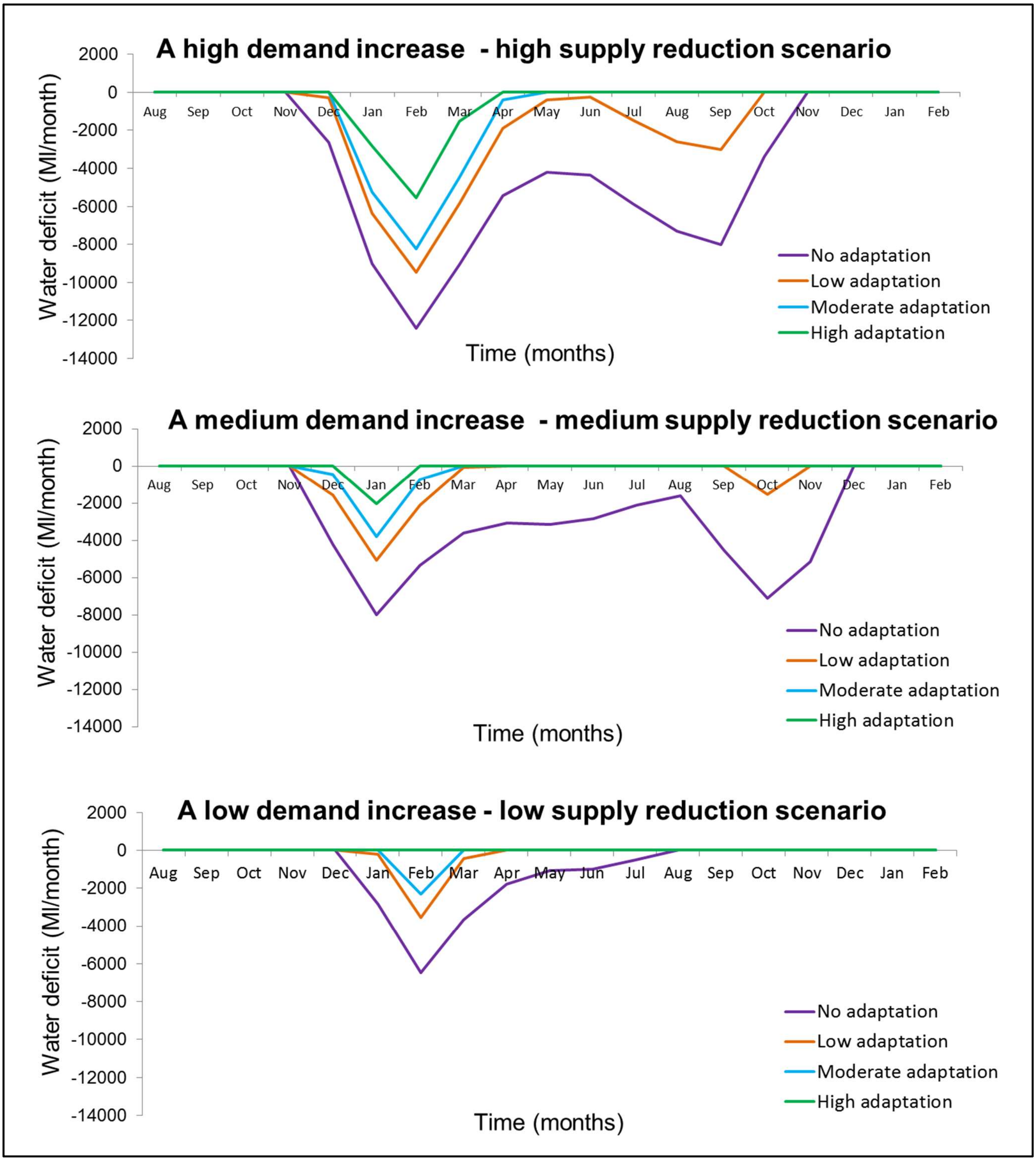

Figure 6.4: Analysis of largest water deficit periods recorded for three isolated scenarios for all adaptation strategies

Figure 6.4 shows how the time to reach the water deficit of greatest magnitude (M3) is constant (for most scenarios) across the strategies and it is the time to recover from largest deficits (M4) that is more variable. It is only possible to observe the above when a water deficit period is separated into the metrics of M3 and M4, i.e. it is not possible to observe this when an aggregate type metric (e.g. M1, M6 or M10) is used, which is what is currently proposed in the literature and utilised in current practice. In addition, Figure 6.4 shows that the duration time of the longest water deficit (metric M2) provides a fairly comprehensive picture of the complete water deficit period without separating out the ‘time to’ and ‘recovery from’ aspects of the deficit period, which, as mentioned previously, can produce variable performance results in the two aspects across the scenarios. Finally, Figure 6.4 shows that the water deficit of greatest magnitude (M7), although highlighted previously as being very sensitive (which is good) also exhibited a fairly uniform reduction across the three scenarios and four strategies. This may not provide the most informative assessment of the deficit periods as they are shown to have a clearly non-uniform variation in the changes in maximum durations of the deficit periods recorded (M2) and time to recover (M3).

The maximum and average magnitudes of water deficits are slightly less variable (by percentage change) but are still good indicators of the adaptation impacts on system performance. The swift time to reach the point of greatest deficit magnitude (exhibited in most scenarios) followed by the longer duration of recovery time, suggests it is individual severe drought months that cause initial water deficit periods to form, which are then recovered from over time. The follow up peaks shown in the high and medium scenarios are caused by repeat severe drought conditions occurring later in the same deficit period. Note that the above cannot be captured by using a single frequency-based or aggregated type resilience metric.

The above observations clearly demonstrate that the choice of metric(s) has implications on the choice of interventions to implement. Decision makers could decide that small or medium magnitude deficit events can be dealt with via water restrictions alone; however, unforeseen extended duration/recovery times could be costly and more detrimental to the system (and to customers) and require more extensive interventions. From this examination at least moderate to high adaptation to the case study system would be recommended to reduce water deficit periods of protracted duration over the more extreme projections (i.e. the high demand increase – high supply reduction scenario in Figure 6.4), whereas only low adaptation may be recommended if targeting a reduction in the magnitude or frequency of water deficits.

6.4 Resilience metrics analysis – correlation assessment

In order to see how the duration, magnitude and frequency metric values cross-over and compare with each other the correlation between individual metric values obtained is explored. This is important as using two highly correlated metrics for resilience assessment is not desirable (as it does not provide additional useful information about the system's resilience).

Figure 6.5 shows the correlation results obtained for the ten metrics analysed across the 60 supply/demand scenarios and four adaptation strategies. As it can be seen from this figure, strong correlations tend to exist within groups of the same metrics types (e.g. M7-M9) and weaker correlations tend to exist across different metric groups.

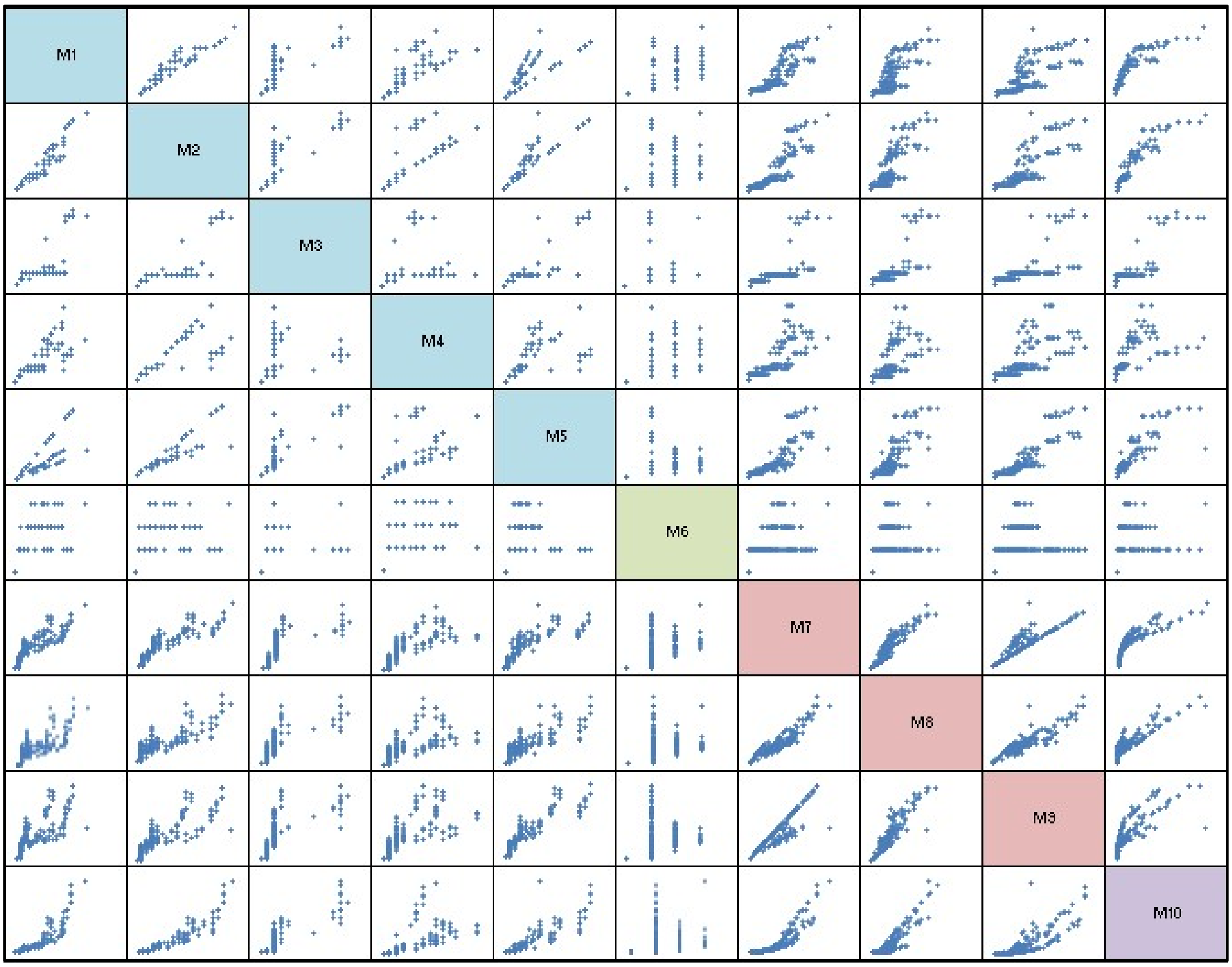

Figure 6.5: Metric correlation results

To further examine the above, the coefficients of determination (i.e. the R^2 values) of each metric correlation are calculated, as shown in Figure 6.6. Note that the R^2 values obtained indicate the proportion of variance between two variables and are scored between 0 and 1 (with 1 indicating perfect correlation between two variables).

(a)

M1									
0.935	M2								
0.526	0.612	M3							
0.739	0.730	0.153	M4						
0.801	0.919	0.624	0.610	M5					
0.306	0.151	0.066	0.209	0.058	M6				
0.804	0.796	0.503	0.636	0.714	0.312	M7			
0.653	0.717	0.603	0.466	0.697	0.177	0.885	M8		
0.670	0.748	0.512	0.554	0.820	0.112	0.878	0.878	M9	
0.791	0.858	0.703	0.480	0.788	0.083	0.710	0.759	0.659	M10

High Correlation	0.8-1
Moderate Correlation	0.5-0.8
Low Correlation	0-0.5

(b)

M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
0.692	0.718	0.478	0.509	0.670	0.164	0.693	0.648	0.648	0.648

Figure 6.6: (a) Coefficient of determination (R2 values) for all metrics; (b) the average of the R2 values for each metric

Figure 6.6 (a) highlights the low correlation between the frequency of water deficit periods metric (M6) with all other metrics. This very low statistical correlation with the other metrics indicates that there is low connection between the changing frequency of water deficit periods and the changing duration/magnitude aspects; however, the frequency-based metric was also shown to be the least sensitive metric, which will inherently reduce the correlation exhibited between this metric and others (as can be seen by the straight lines for M6 on Figure 6.5).This suggests that metric M6 can provide important deficit information that other metrics do not encompass, but also that it cannot predict other performance aspects, so should not be used on its own.

Figure 6.6 (a) also indicates (again) that the metrics with the highest correlation are those within the same group, suggesting that using more than one metric from within the same group is unnecessary. It also shows that the aggregated total volume metric (M10) incorporating both magnitude and duration of deficits has the highest correlation with metric M2. This is suggesting that metric M2 can cover multiple performance aspects in a single criterion of performance, further highlighting its potential as a comprehensive duration based metric and as a potential candidate for a WRM resilience measure.

Taking the average of all R^2 values for each metric reveals the most all-encompassing indicators (Figure 6.6 (b)). It shows that metric M2 has the highest average R^2 value, again indicating that evaluation of this particular duration-based metric provides a wider indication of more system performance aspects in a single assessment. For example, it demonstrates high correlation with the volume metric (M10) mentioned above, as well as all magnitude (M7-M9) and other duration-based metrics (M1-M5). Indicating it can best encompass these multiple individual assessment aspects in a single metric. Information not as well encompassed by the assessment of the other metrics (as displayed in Figure 6.6(b)), include metrics M3, M4 and M6. Additional evaluations of these metrics would be required if the exact characterisation of the time to reach (M3) and time to recover from (M4) the worst magnitude deficits, and the total number of water deficits experienced (M6), was desired.

6.5 Summary

Ten different metrics that could be used to characterise the resilience of a water system (i.e. an adaptation strategy) to a given future scenario of supply and demand were investigated. An in-depth analysis of the metrics was carried out, including an examination of metric sensitivity and correlation, and a detailed examination of the behaviour of water deficit periods, leading to a range of recommendations for the selection of an appropriate resilience-based performance metric. In general it was found that:

1. Multiple metrics covering different aspects of resilience are recommended for providing additional water deficit information, than is presently utilised in current practice.
2. Metric M2 (“the duration of longest water deficit period” metric) stands out as the most all-encompassing and informative performance metric followed closely by metric M7 (“the water deficit of greatest magnitude recorded” metric). However, the analysis demonstrated a relatively high correlation between the two metrics and therefore considering just a

single metric may prove sufficient to evaluate the resilience of a water resource system. A duration based metric would be a more logical assessment metric to use of the two types, as it is the duration of temporary water restrictions that most impact on customers and supply, whereas the magnitude of water deficit events is of less direct concern to customers and water companies so long as the magnitude is maintained within acceptable threshold levels.

3. Frequency type resilience metrics (M6, and in essence M1) cover important aspects/information and would also prove beneficial to measure, as emphasised by the low correlation between M6 and all other metrics; however, metric M6 was also found to be highly un-sensitive and unable to capture the size of 'impact' on the system from water deficit periods, so should not be used on its own.

4. Aggregated type resilience metrics (e.g. averaging metrics M5/M8/M9 or sum/volume type metrics such as M10) are fairly sensitive to different adaptation strategies and supply/demand scenarios but there is also a considerable uncertainty in their calculation due to their nature (i.e. is it a single big or several small deficit periods occurring to give the final values) making it harder to clarify exact adaptation strategy and system performance.

5. Magnitude type resilience metrics (M7-M9) are highly sensitive and provide useful information, especially in terms of proximity to critical threshold levels; however, they do not provide a full picture of deficit events/periods.

6. Duration type resilience metrics are also highly sensitive with "the duration of longest water deficit period" metric (M2) providing the most detailed and informative picture of a deficit event. It is also the metric that exhibits the highest correlation to all other metrics. Splitting the duration of a water deficit period into the time to max peak deficit (M3) and time to recover from max peak deficit (M4) (as suggested in Linkov et al. (2014)) provides more detailed water deficit period information, but the relative performance of each aspect tends to be highly variable when assessed across multiple scenarios of future supply and demand, reducing the clarity of each as a consistent measure of performance.

The above findings are limited to the Bristol case study analysed here. The effect of utilising a single duration (resilience) based metric or a single ‘current practice’ frequency (reliability) based metric for WRM adaptation planning should be examined more in-depth (on additional case studies) to derive if both, or a single metric, is sufficient for effective resilience assessment, i.e. optimal adaptation planning.

Despite several investigations involving resilience criteria (as outlined in section 2.5.7), few to date have applied the metric to a complex real-world WRM adaptation case study under deep uncertainty to identify optimal adaptation strategies from a wide range of potential supply and demand intervention options. Nor has a comparative analysis been conducted with alternative metrics results, i.e. from current UK engineering practice, utilising the more standard reliability metric (frequency of temporary water restrictions). This detailed assessment is now carried out in Chapter 7 where a novel resilience-based methodology for optimal water resource adaptation planning is designed and tested. Based on the results obtained and shown in this chapter, metric M2 is selected for resilience assessment. The optimal adaptation strategy results derived are then compared with a strategy solution derived using current practice, by application of a more traditional frequency based metric (M6).

Chapter 7. Resilience-Based Methodology for WRM Under Uncertainty

7.1 Introduction

The resilience-based methodology and subsequent results and analysis presented in this chapter are under review for publication in Water Resources Research (Roach et al., 2016a).

This chapter assesses whether incorporating a duration-based metric of resilience as a quantified objective in WRM assessments (as identified in Chapter 6), in addition to appraisals of robustness and total cost, can improve the derivation of system adaptation strategies when compared with the standard UK practice of using a system reliability metric in a least cost constrained analysis. A novel resilience-based multi-objective optimisation method is presented that identifies Pareto optimal solutions by maximising water system resilience (calculated as the maximum (longest) recorded duration of a period of water deficit over a given planning horizon) and minimising total adaptation strategy cost subject to target system robustness to uncertain projections of future supply and demand (note the focus on identification of optimal strategies which was not done in the previous chapter). The method is applied to the real world case study of the Bristol Water Resource Zone in the UK (see section 5.4), assessing its applicability at selecting suitable resilient adaptation strategies under climate change and future demand uncertainties.

First the general WRM problem is described followed by the concepts of resilience, reliability, robustness, adaptation strategies and costs. The resilience driven methodology and quantitative case study of Bristol Water is then outlined followed by results and discussion.

7.2 Methodology

7.2.1 WRM problem definition

The WRM problem is defined here as the long-term water resources planning problem of supply meeting future demand over a pre-specified planning horizon under uncertain climate change and population growth. The aim is to, for a given planning horizon, determine the best adaptation strategy(ies) (i.e. set of interventions scheduled across the planning horizon) that are required to upgrade the existing regional WRM system that will maximise the resilience of future water supply whilst minimising the total cost of interventions required subject to target levels of desired robustness. Note here that resilience is now a primary planning objective being optimised for within the methodology, while target robustness is set as a constraint.

The individual performance aspects of resilience, robustness and cost are defined below. Note here that a resilience value is calculated for every future scenario combination tested and robustness is calculated as a single value across all scenario combinations. For example, if 100 combinations of supply and demand scenarios are tested then 100 different resilience results are obtained for a single adaptation strategy examined. Robustness is then calculated as a percentage of those 100 scenarios at which a given level of resilience is maintained.

7.2.2 Resilience of water system and robustness of water supply

A water deficit period was defined in section 6.2.2 as the period of consecutive days/months a water system remains in deficit following an initial water restriction event (e.g. a temporary use ban is put in place due to low supply levels). The implications of extended water restrictions have potentially severe economic, societal, reputational and environmental impacts (as discussed in section 4.2.2.1), with a study by Thames Water estimated that the monthly cost for London alone under restriction would be upward of £7 – 10 billion (Thames Water, 2012).

The circumstances that entail a water deficit event, and subsequent deficit period, occurring are dependent on the system under study. For instance, in the

Bristol Water case study utilised here (section 7.3) a deficit month is counted if the water level in the main network reservoir falls below an unacceptable pre-specified (threshold) level. A water deficit period may be allowed to occur occasionally, in order to manage the water supply system during periods of drought. However, an empty reservoir causing an unfulfilled water demand is deemed unacceptable; therefore, resilience is defined and calculated as the maximum (longest) recorded duration of time taken for the system to enter, and then recover from a water deficit period, without the system reaching complete failure, as shown in equation (7.1).

For example, under a given future scenario if a water deficit period lasts for a single month before being recovered, but is then followed by a water deficit period lasting 6 months, then the resilience of the system is designated as 6 months. Therefore a shorter maximum duration water deficit (e.g. 0-3 months) indicates a higher resilience system, whereas a longer maximum duration water deficit (e.g. 6-12 months) indicates a lower resilience system. The method optimises for a 'minimisation' of total deficit event time hence leads to a 'maximisation' of how quickly a system can recover (i.e. 'bounce back') from a deficit period, i.e. characterised by Hashimoto et al. (1982). The inverse time or probability of recovery is not employed here as this is not easily quantifiable in this instance, as discovered by Moy et al. (1986).

The threshold which defines a water deficit (the vulnerability of the system (Hashimoto et al., 1982)) is pre-specified by setting the water deficit threshold level to an appropriate magnitude. This threshold level varies depending on the system under study. For the Bristol Water system utilised here, this threshold level is linked to the level of water in the combined reservoir system and varies depending on the month of operation, i.e. the threshold is dynamic and is at its lowest (13,610 ML) in the autumn, rising to a more stringent level (30,000 ML) in the spring. However the frequency of deficit periods (the reliability of the system) is left unconstrained in this methodology in order to examine the effect of driving strategy optimisation by resilience alone.

For comparison with the resilience-based methodology described above, a 'current practice' methodology is also tested which represents conventional water company practice of using 'levels of service'. This defines the target frequency that customer water restrictions would be implemented. Rather than using a resilience metric this approach involves setting a target reliability of water supply for the system (here defined as a maximum allowable frequency of water deficit periods recorded over a planning horizon) and then optimising with the same definition of system robustness, calculation of total strategy costs and utilising the dynamic water resource simulation model as outlined below.

Robustness of long-term water supply is specifically defined, as in section 4.2.1, as the fraction (i.e. percentage) of future supply and demand scenarios that result in an acceptable system performance in terms of resilience, as shown in equation (7.3).

7.2.3 Adaptation strategies and dynamic water resource simulation model

Different adaptation strategies can be produced by employing different combinations of water resource options (intervention options) arranged over a long-term planning horizon (see examples and option codes in Table 7.1). The total cost of an adaptation strategy is again expressed in terms of Present Value (*PV*), as shown in equation (7.2). Different adaptation strategies are evaluated using the dynamic water resource simulation model (see section 4.3 for full description), which has been modified to incorporate the resilience-based methodology (see Figure 7.1).

Table 7.1: Intervention options available for the Bristol Water region (Bristol Water, 2014)

Option code	Intervention option	Capital cost (£M)	Operational cost (£M/year)	Deployable output (DO) (ML/d)
	OPTIONS TO REDUCE WATER CONSUMPTION			
C1	Smart metering rollout	11.45	0.06	2.6
C2	Compulsory metering of domestic customers	32.32	2.40	8.0
C3	Selective metering of domestic customers (high users)	5.98	0.32	3.2
C4	Selective change of ownership metering domestic customers	32.45	1.45	11.6
C5	Business water use audits	0.00	0.30	1.0
C6	Household water efficiency programme (partnering social housing)	0.00	0.42	0.4
	OPTIONS TO REDUCE WATER LOSSES			
D1	Pressure reduction	2.47	0.01	2.8
D2	Mains Infrastructure replacement	78.47	0.00	2.2
D3	Communication pipe replacement	36.24	0.00	3.4
D4	Communication pipe and subsidised supply pipe replacement	3.51	0.00	2.2
D5	Leakstop enhanced	1.75	0.00	0.2
D6	Active leakage control increase	0.00	0.91	4.4
D7	Zonally targeted infrastructure renewal	165.08	0.06	13.4
	OPTIONS TO PROVIDE ADDITIONAL WATER RESOURCES			
R1	Minor sources yield improvement	14.68	0.32	1.8
R2	City docks to Barrow transfer scheme	179.42	1.87	30.0
R3	Desalination plant and distribution transfer scheme	179.42	1.87	30.0
R4	Cheddar second reservoir	99.67	0.16	16.3
R5	Purton reservoir and transfer scheme	288.57	4.30	25.0
R6	Pumped refill of Chew Valley reservoir from river Avon	153.81	3.40	25.0
R7	Upgrade of disused southern sources	8.30	0.30	2.4
R8	Effluent re-use for commercial and industrial customers	165.75	1.91	20.0
R9	Avonmouth WWTW direct effluent re-use	185.85	2.07	20.0
R10	Severn Springs bulk transfer	100.94	0.89	15.0
R11	Reduction of bulk transfer agreements	0.00	0.30	4.0
R12	Bulk supply from: (Wessex Water Bridgewater)	26.37	2.31	10.0
R13	Bulk supply from: (Vyrnwy via Severn and Sharpness)	151.95	4.29	25.0
R14	Huntspill Axbridge transfer (traded licence)	10.23	0.14	3.0
R15	Honeyhurst well pumped transfer to Cheddar	5.11	0.01	2.4
R16	Gurney Slade well development	10.70	0.26	1.5
R17	Holes Ash springs re-development	10.22	0.02	0.8
R18	Chew Stoke Stream reservoir	54.81	0.17	8.0

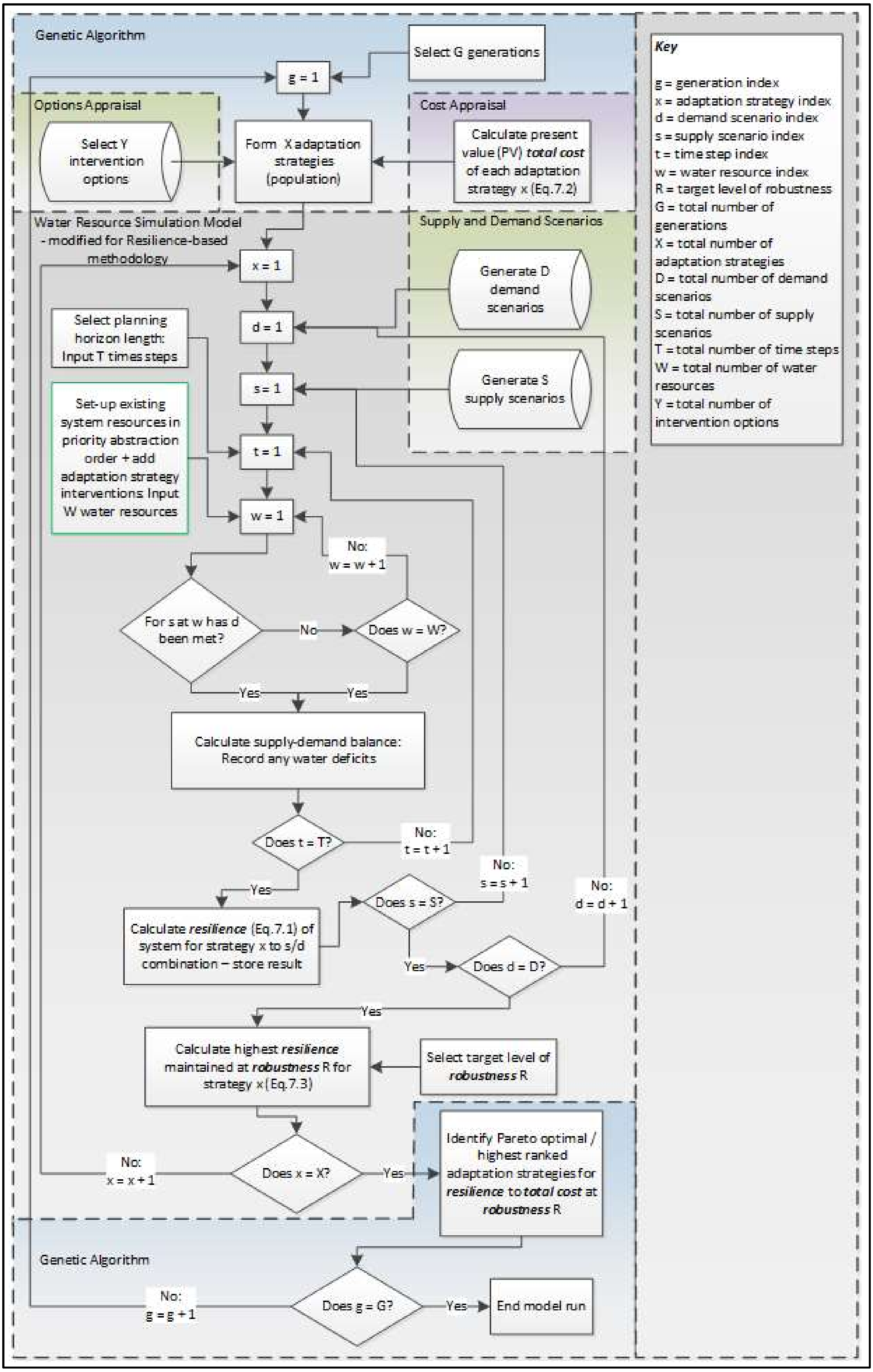

Figure 7.1: Simplified flowchart of the dynamic water resources simulation model – Resilience-based methodology set-up

7.2.4 Optimisation methodology

A two-objective optimisation method (Figure 7.1) is presented that identifies Pareto optimal solutions by maximising system resilience to water deficits and minimising the total cost of interventions, all subject to target level of robustness, i.e. as follows:

The resilience of an adaptation strategy (*x*) to an individual discrete scenario combination of supply and demand (*u*) is calculated using metric M2 from Chapter 6 as:

$$Res_{xu} = \max_{j}\{p(j)\} \tag{7.1}$$

where *p*(*j*) is the duration of the *j*th water deficit period. The total cost of adaptation strategy (*x*) expressed in terms of Present Value (*PV*) is as follows:

$$PV_x = \sum_{y=1}^{Y}\left[\frac{C_y}{(1+r)^{i_y}} + \sum_{i=i_y}^{I}\frac{O_y}{(1+r)^{i}}\right] \tag{7.2}$$

where (*y*) = the intervention option index, (*Y*) = the total number of intervention options in the (adaptation) strategy, (C_y) = the estimated capital cost of intervention option *y* (£M), (O_y) = the estimated operating cost of intervention option *y* (£M/yr), (*r*) = the annual discount rate, (*i*) = the time step of the planning horizon (in years), (i_y) = the year in the planning horizon option *y* is implemented and (*I*) = the total number of years in the planning horizon. A discount rate of 0.045 was selected for this investigation, as utilised by Bristol Water (2014). The robustness of long-term water supply is then derived as follows:

$$Rob_x = \frac{B}{U} * 100 \tag{7.3}$$

where (*B*) = number of scenarios in which the system maintains a given level of resilience and (*U*) = total number of scenario combinations (of supply and demand) considered. Every time an adaptation strategy is evaluated during the optimisation process all potential combinations of supply and demand are generated and assessed using full *enumeration sampling* of all potential scenarios, i.e. the global robustness measure utilised by the Robust

Optimisation methodology in Chapters 4 and 5. This robustness measure is selected as it was analysed as the more favourable from work carried out in those chapters and ensures all viable futures are explored in the robustness calculation.

A target robustness *(R)* is set as a constraint in the optimisation process and the highest level of resilience that can be achieved by a system at greater than or equal to this target level is recorded. For example, if target robustness is set at 80% and the highest level of resilience maintained by a given adaptation strategy system is 5 months, then the system's resilience is designated as 5 months. Note that if multiple optimisation problems (for varying target levels of robustness) are solved this will enable the production of a 3D trade-off surface between resilience, cost and robustness. The same result could be achieved by solving a single three-objective optimisation problem (where robustness is represented as an additional objective rather than a constraint) but this was not done here as this optimisation problem is much harder to solve.

The optimising algorithm selected for this study is the NSGA-II (Deb et al., 2000) from Chapters 4/5. The dynamic, monthly-time step, water resource supply and demand simulation model (see section 7.2.3) is combined with the NSGA-II optimisation algorithm. The model requires three main data inputs; a pool of potential new intervention options (see Table 7.1) from which to form combinations of new adaptation strategies, and the range of potential supply and demand scenarios for a region (see section 7.3.1).

The NSGA-II algorithm automatically forms a population of adaptation strategies, sequences the strategies across the planning horizon and then analyses their resilience across all scenario combinations of supply and demand in the simulation model. The best performing strategies are then carried forward, mutated at random (based on selected probabilities) and then re-analysed over several generations, with the aim of ultimately identifying the Pareto set of results for maximum resilience and least cost for a given target level of robustness where all non-dominated strategy results are discovered. The parameters used for the optimisation analysis are listed in section 7.3.4 and further explanation of the NSGA-II operation can be found in Deb and Pratap (2002).

7.3 Case study

7.3.1 Description and set-up

The methodology detailed in section 7.2 is applied to the case study of the Bristol Water Resource Zone (BWRZ). The full description of this case study is given in section 5.4. The 2,979 future supply and demand scenario combinations are again utilised (see section 5.4.2) as well as the complete pool of BWRZ intervention options (see Table 7.1). The dynamic water resource simulation model is set up for the BWRZ, utilising a monthly timestep and examining a 25 year planning horizon (from year 2015 to year 2039 inclusive). A 25 year planning horizon has been selected to imitate the time frame used in a typical UK water company WRMP planning horizon.

7.3.2 Resilience of water system and robustness of water supply

As detailed in the methodology the resilience of each adaptation strategy under a discrete future scenario of supply and demand is calculated as the maximum recorded duration (in months) that the system remains in a water deficit period (equation (7.1)), due to the remaining water volume in the combined reservoir network falling below a threshold level. The threshold levels are dynamic and vary depending on the month in the year as specified in Bristol Water's drought plan (Bristol Water, 2012).

As there are 2,979 scenario combinations examined, this results in a resilience result for every scenario combination for each adaptation strategy. A discrete target level of robustness is selected (different in different optimisation runs) and the maximum resilience level maintained by each adaptation strategy at or above this selected target robustness is recorded. Note that in the case of the 'current practice' methodology a maximum level of reliability (rather than resilience) is maintained instead.

7.3.3 Current practice methodology application

The target level of reliability for Bristol Water is currently set to maintain a 1 in 15 year maximum occurrence of temporary restrictions being put in place (Bristol Water, 2014). Using reliability equation (7.4) the relative frequency/probability of a system not being in deficit is calculated (Kjeldsen and Rosbjerg, 2004):

$$Rel_{xu} = \left(1 - \frac{\sum_{h=1}^{H} j_t}{H}\right) * 100 \qquad (7.4)$$

where (j_t) = a value equal to 1 if a year contains a water deficit period, otherwise equal to 0; (h) = the year index and (H) = the total number of years in the planning horizon. Note the difference here to the reliability calculation in equation (4.3), where the frequency of water deficit *periods* is now summed rather than the frequency of water deficit *events*. This allows a more direct replication of the BW system reliability targets.

For BW to meet its target Level of Service, this translates as maintaining approximately 93% reliability. Over the selected 25 year planning horizon this corresponds to a maximum allowable frequency of 2 water deficit periods occurring over the planning horizon. This ‘level of service’ must also be maintained over a specified level of a system’s supply/demand balance uncertainty known as target headroom (Environment Agency et al., 2012). Target headroom (see section 2.3.4) is defined as “the minimum buffer that a prudent water company should allow between supply and demand to cater for specified uncertainties in the overall supply-demand resource balance” (UKWIR, 1998) and is calculated by applying probability density functions (pdfs) to all sources of uncertainty in supply and demand (Hall et al., 2012b).

Bristol Water has selected to maintain a target headroom level of 90% over the next 25 year planning horizon in order to significantly reduce the risk of failing to maintain their agreed ‘level of service’ (Bristol Water, 2014). It should be noted that BW’s headroom value is applied to an aggregate supply-demand balance, not directly within a simulation model, and includes factors that are not considered in this study (e.g. risk of outage events of assets). However these are typically smaller components and this study considers a wider range of uncertainty in the supply and demand scenarios which are directly simulated. Therefore BW’s target headroom level, reflecting an attitude to risk, is used by selecting a 90% target robustness of the supply/demand scenarios considered in the resilience driven methodology. It should still be noted though that the two methods differ in that, direct scenario examination is utilised in the methodology presented here compared with the traditional practice of applying pdfs to allow an uncertainty buffer to the overall supply-demand balance.

7.3.4 Application of optimisation model

The dynamic, monthly-time step, water resource supply and demand simulation model with combined NSGA-II optimisation algorithm (as described in section 4.3 and 7.2.4) has been used here. The NSGA-II algorithm parameters used (derived following testing of numerous combinations for optimal optimisation) are as follows:

Table 7.2: NSGA-II parameters selected

Parameter	Value
Population size	400
Number of generations	2000
Selection bit tournament size	2
Mutation probability (per gene)	0.2
Crossover probability (single point)	0.7

Adaptation strategy generation, testing, ranking, mutation and ultimate Pareto strategy identification is an automatic process carried out by the NSGA-II algorithm during the optimisation procedure after 2000 generation assessments.

A range of target levels of robustness are selected and input to the optimisation model as constraints to derive a Pareto set of results. The Pareto sets obtained from multiple optimisation model runs are then combined to produce a 3D-surface of Pareto optimal solutions. The discrete target levels of robustness selected for the optimisation analysis are 50, 60, 70, 80, 90 and 100%. A 'current practice' problem was also solved to derive a single optimal solution under the constraints listed in section 7.3.3.

7.4 Results and discussion

The optimal solution derived by the current practice methodology is presented first, including calculations of the respective resilience exhibited by this strategy over varying target levels of robustness. The resilience driven methodology results are presented afterwards. Selected Pareto optimal adaptation strategies solutions from the resilience driven optimisation methodology are then compared with the current practice derived solution and engineering aspects discussed.

The current practice methodology derives a single optimal strategy solution following low-cost optimisation to a target reliability of ≥92% and target robustness of 90% (see section 7.3.3). The adaptation strategy solution derived has a PV of total cost of £199M and consists of several low cost options to reduce water consumption and water losses and several water transfer schemes scheduled from 2015 to 2017, before construction of a large reservoir at Chew Stoke (option R18 in Table 7.1) in 2021. Only few options are scheduled for post 2021. The full strategy details are shown in Table 7.4.

The strategy derived by the current practice methodology is compared with the resilience driven optimisation model by calculating the resilience of this strategy for the same target levels of robustness applied in the resilience driven optimisation methodology. Figure 7.2 displays the maximum resilience maintained by the current practice strategy under target levels of robustness of 50, 60, 70, 80, 90 and 100% respectively. It shows that this 'reliability' driven strategy can maintain a resilience as high as 3 months for at least 80% of future supply and demand scenarios, but this resilience worsens to 10 and 22 months respectively for 90% and 100% robustness respectively.

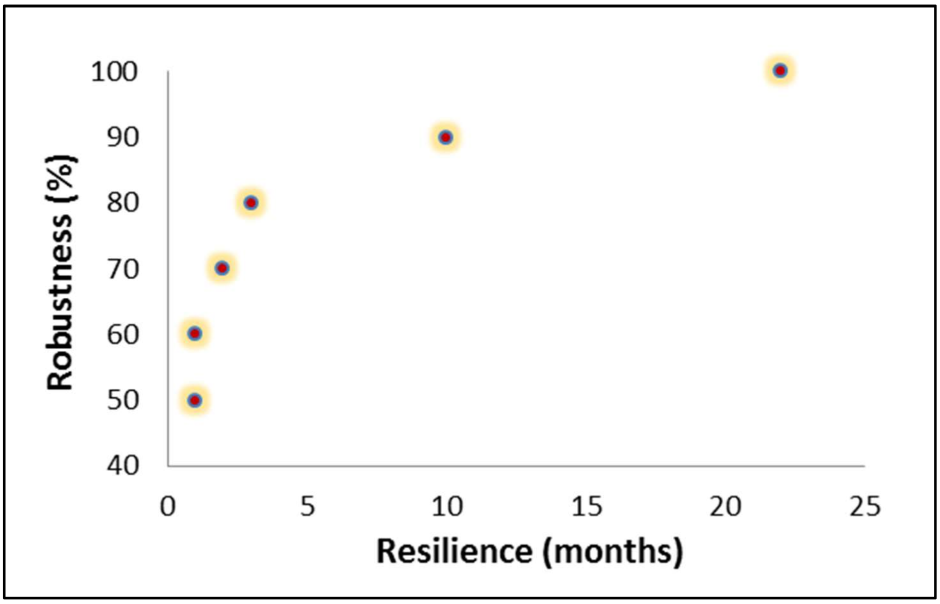

Figure 7.2: Resilience exhibited by the 'current practice' optimal solution at varying target levels of robustness

Pareto optimal strategies were identified by the resilience driven methodology optimised by maximising the system resilience and minimising the PV of the total cost of adaptation strategies. Six separate optimisation runs were conducted for the following target system robustness's: 50, 60, 70, 80, 90 and 100%. Figure 7.3 presents the 3D Pareto set derived from these optimisations run as three 2D graphs displaying: (a) resilience vs cost for varying target levels of robustness, (b) robustness vs cost for varying levels of resilience and (c) resilience vs robustness for varying strategy cost groups. Resilience is also constrained during the optimisation process to derive Pareto solutions to a minimum resilience of 24 months. A system less resilient then this would be highly undesirable hence it was not investigated.

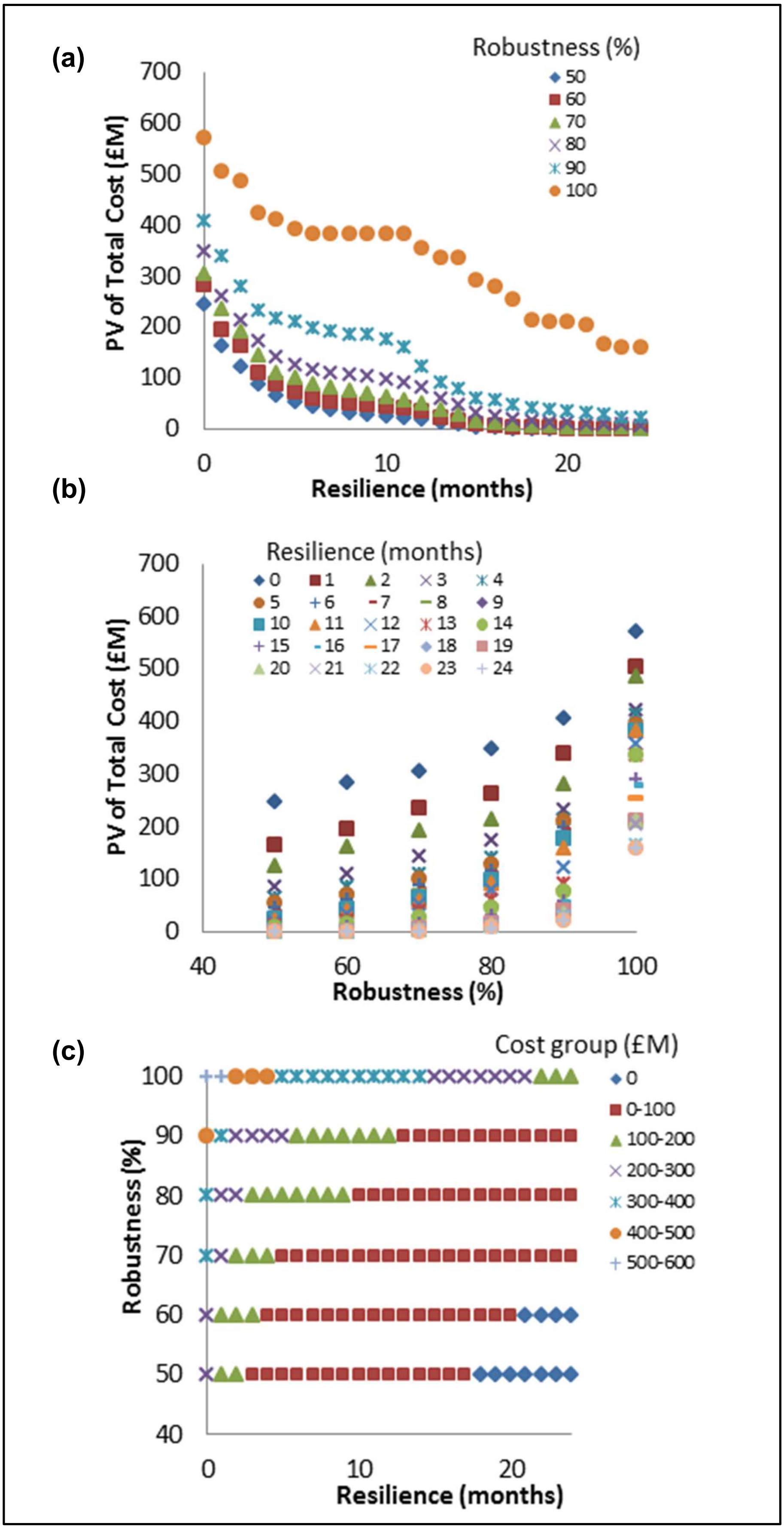

Figure 7.3: Pareto adaptation strategies identified for: (a) resilience vs cost for varying target levels of robustness (b) robustness vs cost for varying levels of resilience and (c) resilience vs robustness for varying strategy cost groups

The Pareto strategies displayed in Figure 7.3 present a trade-off across the three performance indicators. The figures show how increasing the desired target robustness increases the total cost of Pareto adaptation strategies in order to maintain a given level of resilience, with a notable cost increase when attempting to maintain any level of resilience across 100% of future scenarios. The same is evident when attempting to design for a maximisation of resilience, where a resilient system with no failures (i.e. 0 months) shows a notable increase in total costs required. The selection of a preferable adaptation strategy can be made from Figure 7.3 following suitable weighing up of the various performance indicators, however the potential trade-offs are not necessarily easy to visualise.

In order to provide a better visualisation of the three performance aspects a 3D-surface of Pareto optimal solutions is formed by combining all the Pareto sets derived (Figure 7.4). The 3D-surface provides a clearer overview of the various trade-off options and affords a decision maker more perspective about how best to satisfy the various performance criteria. An ideally located individual strategy can then be selected or a specific, more desirable, region of the surface selected for further examination of individual strategies. More specifically, the decision makers can select exactly how robust and resilient they want their system to be as well as being able to discern how moderate increases or decreases in expenditure will alter the performance of the water system. Optimisation to individual target levels of performance, as is undertaken in current UK engineering practice using a cost only optimisation (the EBSD approach (NERA, 2002)), does not allow these observations to be made. Typically only singular optimal solutions are derived (equivalent to identifying a single point in Figure 7.3 (a-c)).

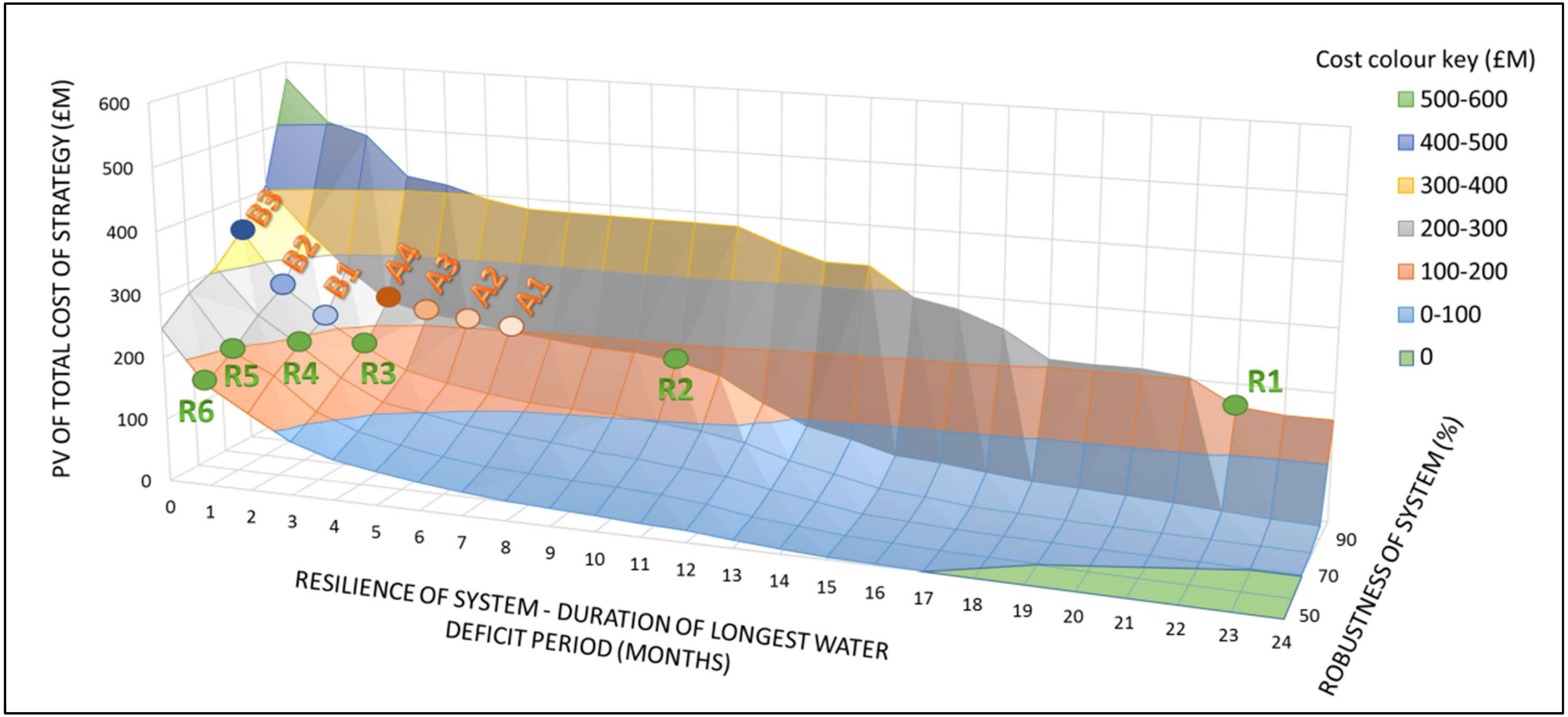

Figure 7.4: A 3D-surface of Pareto adaptation strategies identified over performance indicators of resilience (0-24 months), robustness (50-100%) and PV of total cost (0-600 £M); for discrete target levels of robustness of 50, 60, 70, 80, 90 and 100%. Including individual strategies selected for further analysis (R1-R6, A1-A4, and B1-B3)

The current practice derived optimal strategy is compared with selected strategy solutions derived by the resilience driven methodology. Pareto solutions for this comparison are selected from the surface that exhibit similar levels of resilience / total costs to the current practice strategy in order to contrast and compare the solutions derived by each method. The strategies selected are shown in Figure 7.4. They consist of: strategies R1-R6, which are selected as they exhibit the same resilience to target levels of robustness as the current practice solution (i.e. from Figure 7.2), and strategies A1-A4 and B1-B3 as they offer increased resilience at a high level of robustness (90% for strategies A1-A4 and 80% for strategies B1-B3) for a similar PV of total cost as the current practice solution. Table 7.3 lists the PV of total cost of each strategy examined as well as the resilience and reliability exhibited, the respective levels of robustness and the average resilience and average reliability recorded across all future scenarios examined.

Table 7.3: Cost, resilience, reliability and robustness exhibited by the selected strategies

Strategy information	Strategy ID	Total cost - PV (£M)	Highest relibaility maintained over 90% of scenarios (%)	Scenarios maintained at reliability of ≥92% (%)	Resilience maintained over varying % target levels of robustness (months)						Avg. resilience (months)	Avg. reliability (%)
					100%	90%	80%	70%	60%	50%		
Strategy derived by Current Practice (CP)	CP	199.0	92	90	22	10	3	2	1	1	2.4	95.6
Strategies derived from resilience driven methodology												
Of matching resilience (R) to CP strategy	R1	165.1	80	64	22						4.4	91.2
	R2	175.7	84	71		10					3.1	92.8
	R3	173.6	88	76			3				3.0	93.2
	R4	191.1	88	80				2			2.8	94.0
	R5	195.2	88	86					1		2.7	94.8
	R6	163.2	84	78						1	2.4	94.8
Of similar PV of total cost to CP strategy	A1	198.3	88	81		6					2.4	95.6
	A2	209.6	88	87		5					2.2	96.0
	A3	214.8	88	87		4					2.1	96.0
	A4	231.3	92	93		3					1.8	96.8
	B1	214.0	88	87			2				2.1	95.6
	B2	261.6	92	96			1				1.6	97.6
	B3	349.1	96	99			0				0.9	98.8

Comparing the current practice optimal strategy with the R1-R6 Pareto optimal strategies in Table 7.3 shows that, for a lower PV of total cost, solutions are generated with the same resilience as the current practice strategy for the varying target levels of robustness. For example, strategy R3 has the matching resilience of 3 months over 80% of future scenarios whilst costing approximately £25M less than the current practice strategy. The trade-off is a slight decrease in reliability of water supply, with strategy R3 maintaining a reliability of 88% over 90% of future supply/demand scenarios as opposed to 92% in the case of the current practice strategy.

Strategy A1, the solution of most similar total cost to the current practice solution produced a more resilient system, with 90% of future scenarios now maintaining a resilience of 6 months, in contrast to the 10 months exhibited by the current practice solution. The trade-off again is a moderate reduction in reliability, with strategy A1 maintaining a reliability of 92% over 81% of future scenarios, which falls to 88% over the remaining 9% of future scenarios within the 90% target robustness region. This demonstrates that the resilience driven methodology has identified an adaptation strategy that provides a much more resilient, but marginally less reliable system than the one identified by using the current practice.

Strategy solutions A2, A3 and B1 can further increase the resilience of the system for around 5% increase in overall total costs. Strategy solutions A4, B2 and B3 increase both the resilience and reliability of the system for increased overall costs. The above demonstrates that an optimal solution across all three performance indicators can only be identified from the resilience driven methodology as opposed to current practice, whereby singular optimal solutions to fewer objectives are derived. If the priority design criterion for a water supply system is to maintain high reliability then this could be set as a constraint and still maintained at a high robustness. However the benefit of the resilience driven methodology is it allows a more resilient system to then be identified in addition to just using reliability, albeit at a potentially increased PV of total cost.

Table 7.4 lists the individual intervention components for each analysed strategy and their time of implementation within the 25 year planning horizon (codes for individual intervention options located in Table 7.1). It shows that the current practice reliability driven strategy solution includes a greater number of low cost intervention options early in the planning horizon (2015) with the most costly intervention option (R18 – a new reservoir at Chew stoke) not implemented until 2021. This strategy also includes no interventions later on in the planning horizon (2029-2039), implying that a number of less costly interventions selected early on in the horizon greatly improves system reliability. Opposite of this, the alternative strategies derived by the resilience driven methodology recommend a high cost intervention early in the planning horizon (either R4 – a reservoir at Cheddar, R18 or, for the most resilient strategy (B3), R3 – a small desalination plant), before distributing a number of lower cost interventions over the remaining planning horizon, right up to 2039. This suggests larger investment early on in the planning horizon as well as regular smaller water resource additions to the system increases overall system resilience, as the duration as well as frequency of severe drought periods are projected to increase over time due to climate change.

Table 7.4: Table of intervention option components and their year of implementation for selected strategies (option codes listed in Table 7.1)

Strategy code	CP	R1	R2	R3	R4	R5	R6	A1	A2	A3	A4	B1	B2	B3
Year of option implementation														
2015	C1 C3 C4 D1 D4 D6 R14		D4 D6	D1 R15 R18	R4 R15	C3 D1 D4 R4	C1 D1 D4 R11 R12	R11 R15	C4 D1 R11	C4 D4	C4 D6 R11	C1 R4	C4 R4 R11	D1 R3 R11
2016		D1	C3 D1 R4 R11	C3 C4 D4 R11	R11 D1	R15	R15	C3 D1 D6 R4 R14	D4 R4	C3 D1 R4 R11	C1 D4 R4	C3 C4 R11	D1 D4 R18	R4
2017	R11 R15	C3 C4 D4	R15		C3 C4	R11	D6 R7	C1 D4	R14	R14 R15	C3 R15	D1 D4	C3	D4 R15
2018						R14			C3 R15	C1	D1	R15		
2019														
2020		D6 R11												
2021	R18													
2022							C4							
2023		C1												
2024														C3
2025													D5	
2026	C5	R12			D4	R12	R14						R15	
2027		C2		D6										
2028	R7											D5		
2029											R14			
2030									C1 D6					
2031			C4	C1 R12		C4	C3	C4		D6	R12	D6 R14	R14	
2032														
2033		R7 R14			R14	D6							R12	
2034			R12					R12						D6 R14
2035														
2036														
2037					R12							R12	D6	C4 C5
2038		R16		C5					R12	R12				
2039						D5	C5						C5	
PV of total cost (£M)	199	165	176	174	191	195	163	198	210	215	231	214	262	349

Figure key

- Very high cost intervention options > £150 M capital cost
- High cost intervention options > £100 M capital cost
- Medium cost intervention options > £50 M capital cost
- Low cost intervention options < £50 M capital cost

Figure 7.5 demonstrates the system capacity increases (water supply capacity added to the system) provided by the CP strategy and two similarly priced strategies A1 and B1, over the 25 year planning horizon (details of intervention options selected are shown in Table 7.4). It highlights how the outputs from the 'levels of service' method and the resilience driven method differ considerably in the size and timing of intervention options recommended.

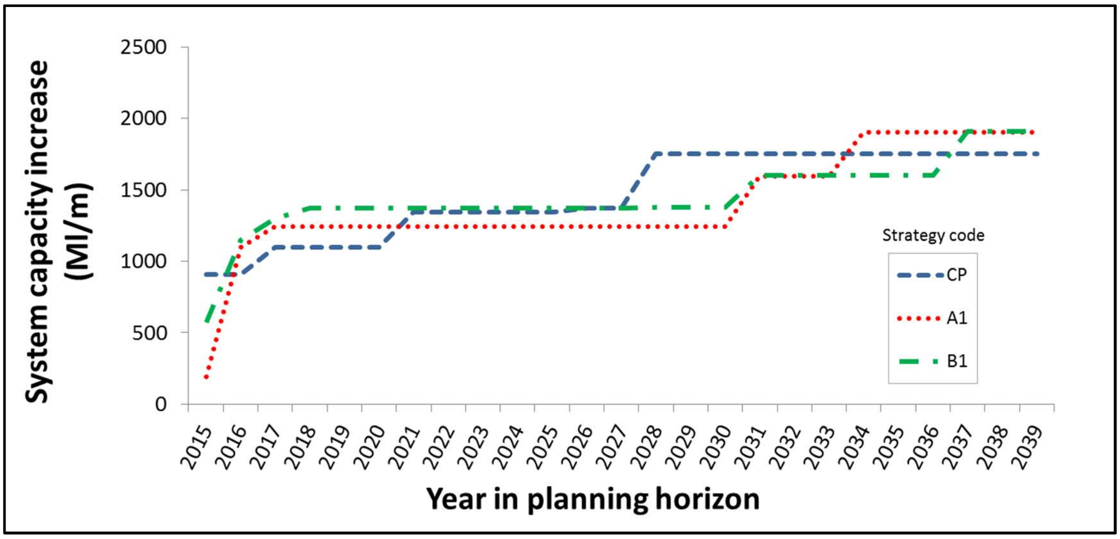

Figure 7.5: System capacity increases for the current practice (CP) strategy and resilience driven strategies A1 and B1

The results obtained here demonstrate how simplifying a planning approach to optimise to a single criterion (i.e. cost subject to target reliability) does not provide solutions that perform optimally across alternative criteria. Current UK engineering practice that utilises a single target level of reliability does not explicitly consider the resilience of the system. For instance, a water system may maintain its target level of a 1 in 15 year risk of water deficit occurring, however this assessment does not explore the length of time these deficit periods may last. A prolonged single water deficit period may be as detrimental to the system and its customers as a higher frequency of smaller deficit periods. The methodology proposed here produced a wide range of Pareto optimal strategies to the performance indicators of resilience, robustness and cost and allows a decision maker to select a strategy based on their final preferred trade-off across these criteria.

Driving the optimisation by resilience allowed the identification of multiple solutions that trade-off marginally reduced reliability for significantly improved resilience when compared to the existing practice. The variation in strategy solutions derived in this study highlights that resilience and reliability lead to differently designed systems and therefore by considering both performance indicators it may be possible to derive a solution that performs well across both metrics (see Figure 7.5). A future development to explore in this method would be to constrain the resilience driven optimisation to maintain a desired target reliability in order to derive the most resilient as well as adequately reliable solutions, or alternatively optimise the system to all four objectives simultaneously. This would identify a surface of Pareto solutions with increased total costs to account for the additional constraint but also an increased number of strategy solutions. However this would be a worthwhile trade-off to ensure more reliable and resilient water systems in the face of future uncertainties.

7.5 Summary

This chapter has presented a comparative assessment of a new resilience-based methodology for WRM planning that optimises for resilience and cost for a given target level of robustness, with that of a more conventional engineering approach. A candidate metric for measuring water system resilience is defined as the maximum recorded duration of a water deficit period and its impact assessed on a real-world WRM adaptation case study of Bristol Water.

The results obtained in this case study demonstrate that the new approach improves on key industry planning issues by increasing the transparency of adaptation strategy assessment processes and improving the information available to decision makers. The method also improves on the economic cost appraisal of water restriction periods, as a duration of deficit is more easily quantifiable than a frequency-based approach. The resilience methodology created a 3D surface of Pareto-optimal solutions providing decision makers with a more complete trade-off picture of what different planning strategies can achieve in terms of system performance benefits and related costs thus enabling them to make better informed decisions.

In addition to the above observations, a comparison of the new methodology with the current UK planning practice on the same case study resulted in further observations as follows:

1. Optimising for a single objective in the current practice methodology yields only a single solution that is highly dependent on the initial target robustness (headroom) and target reliability selected and does not provide alternative solutions that may achieve benefits for small trade-offs.
2. The strategy solution derived using the current practice methodology produced in the real-life case study analysed a less resilient system than the similar costing solutions identified using the proposed resilience driven methodology. Whereas the resilience driven strategies were less reliable (although not by much), suggesting that trade-off exists between the two.
3. In order to better explore the trade-offs that may be gained by considering both resilience and reliability, it is recommended that the resilience driven methodology is further developed with the inclusion of a reliability criteria as an additional objective or constraint in the approach presented here.
4. The resilience driven methodology yielded planning strategies which space interventions more evenly across the planning horizon when compared to the current practice (reliability driven) strategy solution, which scheduled more lower cost interventions earlier in the planning horizon. This suggests that, at least in the case study analysed here, more low cost interventions early in the planning horizon achieve higher system reliability whereas regular intervention options spread over the planning horizon achieve higher system resilience when planning to an uncertain future. Examination of both metrics is recommended if optimisation of the additional system attribute (resilience) is desired in future UK practice.

Chapter 8. Considerations for Future WRM Framework

8.1 Introduction

The work carried out throughout this study has led to a range of specific conclusions, both qualitative and quantitative, in relation to isolated methods and metrics for application to improve WRM adaptation planning under deep uncertainty. The findings ultimately reveal that a more diverse range of tools and approaches should be utilised to improve on the approaches being exploited in current engineering practice, ideally identified following further quantitative examples and pilot studies. An update in WRM adaptation planning approaches is supported by the increasing evidence of non-stationarity in the world's climate and the growing complexity of projecting future levels of regional population growth and associated water use. The approaches explored here highlighted several superior DMM characteristics and beneficial supplementary metrics of performance leading to a number of recommendations (as detailed in each Chapters conclusions). Although no single definitive answer can be objectively given here on how best to update the UK water industries planning approaches, the findings from this research can help consolidate a "minimum standard" list of aspects that should ideally be considered when approaching WRM adaptation problems under uncertainty in the future.

8.2 Minimum standards for a future WRM framework

Based on the reviews carried out and case study results obtained in Chapters 2-7, the ideal framework for long-term WRM planning under uncertainty should include or facilitate the following:

1. <u>Define and use multiple objectives.</u> This is imperative if the industry plans to advance from the current EBSD method and move away from single point linear least-cost optimisation which limits output data. Consideration of multiple objectives leads to identification of multiple, detailed and often complex, trade-offs. This was revealed in both the IG/RO case study investigations (Chapter 5) and in the resilience-based methodology

examination (Chapter 7), which in both cases concluded that pre-specifying a single linear projection of future supply and demand (as in the current EBSD method), or constraining a system to specific objective values, leads to the output of only a single optimal adaptation strategy, effectively determining only a single point on Pareto fronts or surfaces identified by the DMMs. Analysing multi-objectives provides additional trade-off information that can be used to make better, more informed decisions.

2. Utilise optimisation algorithms. The Bristol Water case study explored in Chapter 5 concluded that optimisation algorithms were a necessity, even for DMMs that typically carry out pre-specified strategy assessments (i.e. Info-Gap), if a large pool of potential intervention options is considered (which is normally the case in practice). Ideally, state-of-the-art algorithms should be applied to maximise the chance of identifying optimal solutions and to minimise model run times. The optimisation algorithms should be efficient and reliable but also able to handle multi/many-objectives (see above) in order to facilitate comprehensive adaptation strategy generation, evaluation and eventual Pareto optimal strategies discovery. This increases the range of output information for the decision maker and allows a detailed, visualised and hence more transparent trade-off examination of optimal strategies.

3. Incorporate complex simulation models into planning process. The dynamic water resources simulation model developed in this thesis and utilised by the DMMs on the two case studies (Chapter 5) and the subsequent resilience-based study (Chapter 7) was able to carry out detailed performance assessments of metrics such as resilience and reliability (i.e. analysing the exact duration and frequency of water deficits) because of the dynamic daily/monthly simulation of the supply system replicating a real-life continuously fluctuating supply-demand balance. Non-simulation based assessments of water resource systems (i.e. as in the current EBSD method, which uses single annual numbers of supply and demand rather than dynamically simulating the balance over the planning horizon) are unable to analyse these specifics and so cannot explore the system level benefits of specific options. The growing

complexity of WRM problems means water resource planners need to move towards simulation-based assessments in order to fully understand the interactions between different options/strategies over different futures.

4. Employ improved uncertainty characterisation and assessment. The current practice EBSD method of applying probability distributions to uncertain variables in order to derive a single target headroom level has been deemed fit for purpose in the past but its limitations have been quantified in the case studies presented here. Namely its inability to investigate, and thus be strengthened against, potential variations in the central supply and demand estimations utilised (shown in the Bristol Water case study in Chapter 5 when the preferred Bristol Water plans were tested in the RO and IG models and exhibited lower robustness then the Pareto optimal strategies derived by the given DMMs when a wide range of future scenarios were examined), as well as the inability of the headroom methodology to facilitate trade-off examinations of the uncertainties due to its singular derived projection in the supply-demand balance. The headroom methodology also does not utilise simulation assessments (see above), and so cannot be used for precise deficit evaluations (i.e. calculations of resilience as defined in Chapter 7). Analysis carried out in Chapter 5 highlighted the additional benefits of assessing a range of different plausible futures in the form of pre-defined scenarios of supply and demand. Scenarios were used to represent a wide range of climate change and population growth uncertainties and allowed a greater examination of how different adaptation strategies perform under different futures. This allowed the identification of a range of optimal strategies for varying levels of robustness to the array of plausible scenarios, allowing beneficial trade-off examinations. Scenario assessments also permit a more transparent and defendable calculation of robustness to uncertainty (see below). Therefore it is recommended that water resource planners move away from single estimate headroom projections and utilise either a wide range of plausible scenarios or apply an intelligent method of scenario discovery to reduce the range of examined conditions, but still ensuring that the extremes are suitably observed.

5. Include an explicit robustness examination. Current UK WRM planning methods do not explicitly calculate a level of system robustness. The global (RO) and local (IG) robustness measures examined on the case studies in Chapter 5 proved highly informative in indicating a strategies ability to maintain a target level of performance over a wide range of different futures. The robustness measures utilised were easily applied and calculated within the simulation model and could easily be set either as a direct optimisation objective (see Chapter 5) or as a constraint in the optimisation process (see Chapter 7). From case study work carried out in Chapter 5 it was concluded that Robust Optimisation utilising a global robustness analysis is preferable to an Info-Gap local robustness analysis, as the local analysis proved more problematic when applied to a wide range of discrete scenario projections that were not monotonically increasing.

6. Incorporate additional performance metrics. The study carried out in Chapter 7 indicated the benefits of examining an additional metric of resilience (i.e. a duration-based assessment criterion) in WRM adaptation planning. The metric examined not only identified Pareto optimal strategies that minimised the maximum duration of water deficit periods but the strategies derived were also highly reliable (maintained a low frequency of water deficits occurring). The results indicated however, that ideally both a metric of resilience as well as reliability should be utilised in order to maximise the performance of adaptation strategies to both performance aspects and address related trade-offs. Using a duration and frequency assessment metric would also allow easier quantification of the projected 'cost' of water deficit periods over a planning horizon, thus enabling water companies to perform smarter cost-benefit planning.

7. Increase the transparency of adaptation strategy assessments. This aspect links in with the item 6 above as improved metrics for performance analysis will greatly increase the transparency of the adaptation strategy assessment process. However, this section also includes features that reduce the clarity of the assessment process and could be improved, such as reducing indistinct and ambiguous terminology often prevalent within water resource management plans (as discovered in Chapters 2 and 3),

as well as avoidance of indistinct metrics of performance, i.e. metrics that amalgamate, normalise or include integrated complex risk calculations (as ascertained from Chapter 6). This includes multi-criteria analysis processes within company WRMPs which weight particular performance aspects of options (i.e. environmental/social impact) in an often amalgamated and ambiguous form, which cause some options to be dismissed before potentially beneficial trade-offs can be examined. The current EBSD 'levels of service' approach also utilises a range of complex calculations and assumptions often buried deep within company WRMPs, which prevents complete clarity of the strategy assessment process for different stakeholders and customers. From the comparative investigation between the resilience-based methodology and the representation of current practice in Chapter 7, it was shown that the single optimal strategy identified by the current practice method prevented any further examination, and as such, any further debate on the suitability of the strategy identified. This places complete faith in the initial headroom selection and the specific level of service selected, which as discussed, can lack transparency in their exact calculations. Whereas the resilience-based method produced a whole surface of optimal solutions that could be further examined and debated until a preferred strategy is selected that satisfies all parties involved.

8. <u>Provide improved visualisations of trade-off examinations.</u> The resilience-based methodology in Chapter 7 led to the formation of a 3D surface of Pareto optimal adaptation strategies across the objectives of resilience, cost and robustness. This provided an improved visualisation of the trade-offs between the various performance aspects and highlighted how current planning approaches could benefit from applying similar concepts, especially within future company WRMPs. Improved visualisation of outputs will be particularly important as assessment and modelling/simulation processes inevitably get more complex. Outputs from multi-objectives can produce hundreds of optimal solutions across the objectives and will require smart screening/visual methods to isolate preferred strategies. Simplifying the trade-off evaluations will be vital in steering decision makers in the water industry to making appropriate

decisions across multi-objectives. Improved output formats also make final decisions easier to communicate to different stakeholders and customers.

9. Deliver a manageable step change from current practice. In order to trial and eventually include updated practices, such as detailed simulation testing, a manageable step change from current practices must be applied. This will include simplifying often complex DMMs into easily adaptable decision tools for use by all water companies that can be incorporated into existing modelling software and data. A complete overhaul of all existing planning methods could lead to an increased lack of confidence in the WRM adaptation planning process, therefore a paced induction of new decision making method/tools may be preferable to more easily gauge the improvement (or decline) in planning performance brought about.

10. Include a more thorough optioneering investigation. A more thorough, or 'smarter', optioneering/screening appraisal would be beneficial in a future WRM framework. This 'smarter' optioneering process should include a more in-depth analysis into options that can inherently reduce uncertainties, i.e. such as less 'climate vulnerable' resource options; more 'flexible' solutions; assessment of options outside of a company's boundaries (inter-company cooperation/collaboration) and taking advantage of more advanced resource technology (see section 8.3).

11. Encourage more inter-sector cooperation and collaboration. This could be one of the more significant step changes in WRM adaptation planning as it would tie in other sectors, such as energy and agriculture, to evaluate opportunities to improve all sectors simultaneously. Future frameworks should include more inter-sector cooperation and collaboration to improve true long-term resilience/robustness across all vital societal systems, i.e. more consideration of the water-food-energy nexus and potential multifunctional features of water resource options (see section below).

8.3 Engineering smarter adaptation: additional considerations

In the previous section a list of minimum standards for a future WRM framework were detailed. This included a number of suggestions derived directly from work carried out in this thesis (Chapters 2-7); however, two of the items (no. 10 and 11), were derived indirectly from the work carried out here but are important planning aspects that should undergo further consideration to enhance adaptation planning procedures and improve the overall robustness/resilience of future water resource systems. A discussion into the various aspects detailed in those two sections now follows.

So far this study has concentrated on the specific characteristics and features of the selected decision approaches being considered for use in the water industry; however, there has been no examination of alternative practical approaches, techniques or options for increasing overall water system robustness or resilience to uncertainty. For instance, engineering solutions that inherently reduce uncertainties to future climate events or beneficial intervention options that exist beyond a water company's boundaries (Defra, 2016a). Water companies should consider every feasible option/strategy available to best balance future supply against demand with greater consideration of the long-term benefits (beyond the current UK 25 year planning horizon) and employ a more in-depth analysis of the hidden threats and indirect uncertainties that could impact a network. These additional considerations should ideally be incorporated into future adaptation planning frameworks and the optimal approach for doing so warrants additional study. These additional engineering considerations include the following unconventional adaptation approaches:

8.2.1 Multifunctional water resource options

In 2011 a research group was set up in the Netherlands between the STW research group and the universities of Delft, Twente and Wageningen for the assessment of "Multi-functional Flood defences (MFFD)" (STW, 2016). During the completion of this STREAM EngD project I acted as the ambassador for HR Wallingford to the MFFD group, attending several meetings to hear the progress of the research projects, share ideas and discuss areas for collaborative study. The research presented at the meetings was innovative and showed potential for application elsewhere in the water industry. However, to date, the concept of multi-functional water resources has no established research group and is a concept not examined in detail within UK water industry WRMPs. Nonetheless, examples exist that highlight the potential for greater consideration of the planning concept to improve the resilience of multiple sectors simultaneously, i.e. to look beyond the scope of simply satisfying a supply and demand balance and examine multifunctional benefits of resources.

Additional functions that could be exploited include: flood relief capabilities, social (i.e. leisure and tourism) benefits, conservation/environmental payoffs and the nexus of water, food and energy (Hoff, 2011). The water-food-energy nexus is multidimensional and highly complex in nature (Howarth and Monasterolo, 2016) and to comprehensively combine the management and organisation of all sectors simultaneously may be overly ambitious. However, a transdisciplinary approach to knowledge development across the various sectors may be needed to effectively inform the decision making processes to build true long-term societal resilience to future deep uncertainties that goes beyond the divisions of current planning and research practice.

One example of a multifunctional water resource design is found within Essex and Suffolk Water (a UK based water company) who have recently enlarged the Abberton reservoir to increase its storage capacity by 58% to, as they state: "make Essex's water resources more resilient to the effects of climate change" (Essex and Suffolk Water, 2014). The scheme takes advantage of the vast wetlands surrounding the reservoir by transferring water from these often flooded regions during wetter periods to the now enlarged reservoir area. The effect is reduced flooding during wet periods while simultaneously providing more water for use during periods of drought, in turn reclaiming and improving nearby farmland and agricultural outputs.

This type of multifunctional engineering option may not necessarily feature in the Pareto optimal adaptation strategies identified when optimising only for a least cost - highly robust strategy examined over a constrained set of climate futures; however, the option provides numerous additional benefits, including many environmental and social co-benefits. Alternative options providing similar deployable outputs for less capital cost may be available to the planners; however, some of these options (e.g. additional river abstractions on an already tapped river) can be precarious if placing additional stresses on already exploited water sources. These often “smaller scale” resource options can initially appear more cost effective but may have the drawback of concentrating a large volume of a systems water supply on the reliability of individual key sources or offer no additional benefits. This reduces the robustness of the system to an aspect of uncertainty not typically examined in detail in current practice.

8.2.2 Interconnection of resource networks

Defra’s recent report on enabling greater resilience in the water sector highlighted the benefit of including long-term national assessments to reveal more options for balancing supply and demand then are currently examined on a regional/company level (Defra, 2016a). For example, to encourage more collaboration between neighbouring companies to improve ways to trade water, and possibilities to develop large-scale joint water supply infrastructure to supply multiple companies/regions simultaneously.

United Utilities, a large UK based water company, are currently considering plans to construct a series of pipelines between West Cumbria and the Thirlmere Reservoir, one of the company’s largest water resources (Figure 8.1). If this strategy is employed it would form the UK’s largest interconnected water resource zone (United Utilities, 2014); however, due to its high capital costs this option would not be readily selected using the more simplistic EBSD or alternative least-cost optimisation forms. Nevertheless, the connective pipeline option allows the transfer of water to any diminishing supply area in the region and would provide enough water to fulfil projected customers’ needs well above forecasted demand levels. The interconnection of resource zones would not only provide increased resilience for long-term supplies but also provide additional supply to cater for (and encourage) future energy generation and agricultural/industrial developments in the area. The transfer would also enable existing resources in West Cumbria to cease and thus return the local habitats to more natural conditions, improving regional conservation. Selection of this adaptation strategy would procure benefits for the water-food-energy nexus within the region whilst providing increased long-term robustness and resilience for the West Cumbria water supply. This form of strategy innovation, spending more in the short-term to increase long-term benefits across a range of sectors and services needs to be more thoroughly considered in future adaptation planning frameworks.

Figure 8.1: Map of proposed interconnecting pipeline option for West Cumbria (image adapted from United Utilities (2014))

Additional propositions for large scale inter-connection of resource networks in the UK exist including the ambitious national grid concept (AECOM, 2014). This option involves directing water from the precipitation rich Scotland into Kielder Reservoir in the North of England before channelling it down through West England using the natural topographical curvature of the country to ultimately irrigate the South East of England (Figure 8.2). The boldness and numerous benefits of this plan (from increased nationwide water security to wide ranging energy, agriculture, leisure and tourism opportunities (see section 8.2.3)), are offset by its enormous price-tag (projected around £14bn capital cost by AECOM (2014)). However, if the UK and other nations are looking to develop planning frameworks that ensure adequate robustness to future uncertainties are maintained in the most water scarce regions of the country then this sort of "outside the box" (or rather "outside the company resource zone") thinking is to be encouraged to develop more "collaborative" future planning frameworks. This should include examinations of options to reverse the privatisation of water industries around the world.

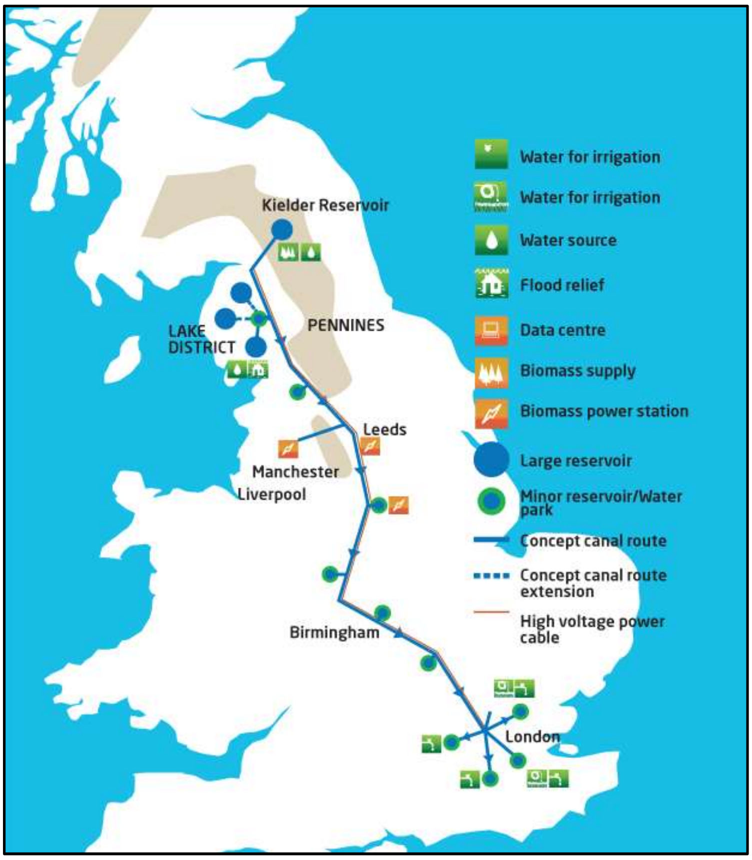

Figure 8.2: Map of proposed national water grid between North and South UK (map taken from the Chartered Institute of Building, (2013))

8.2.3 Collaborative planning and management

The recent Defra water sector resilience report (Defra, 2016a) called for increased consideration of collaborative opportunities between neighbouring water companies and across sectors. Since privatisation of the water industry in England and Wales in 1989, water resource management across the UK has been a highly fragmented practice. This has been mirrored across the world with the majority of nations opting for full privatisation following the UKs example, with each segregated company largely consolidating its plans within its boundaries with only moderate consideration given to inter-basin transfers and resource sharing opportunities. Inter-sector collaboration will be particularly essential in the future but currently receives limited examination in water resource management plans. Despite this a few examples are beginning to surface where companies have taken this initiative. Examples include: Kent County Council who are currently working with Southern Water, South East Water, farmers and growers to explore the potential for collaboration (Southern Water, 2016), as well as the East Anglia Water resources group who are bringing together water companies, farmers, the energy sector and others to work together to improve water resilience over the long-term (Defra, 2016a).

The advantages of providing surplus water supplies available for energy and agricultural growth have far reaching economic and social benefits that warrant further examination and analysis. The most important step-change in future WRM planning approaches could be an updated mechanism for inter-sector management, as increasing the performance (e.g. the resilience, reliability, robustness) of one sector will inherently increase the performance of another (e.g. energy, agriculture). Inter-sector collaboration should also include more cooperation between applicatory scientific bodies and worldwide water industries in order to provide precision data and advisable information to companies on the risks to water availability in their catchment regions over the long term.

8.2.4 Flexible water resource options

Flexible water resource options include those that have the capability of being updated in scale and deployable output if and when required as more information becomes available in the future (i.e. as uncertainties reduce over time). This includes resource options such as multi-scale reservoirs or desalination plants that have the potential to be increased in total capacity/output over time, e.g. the Abberton reservoir example in section 8.2.1. The main trade-off of this approach is reduced initial capital costs in the short-term for long-term flexibility, but often in exchange for reduced short term robustness. However, this is dependent on such flexible options being available to decision makers.

The main difficulty with flexibility assessments is in making a true reliable valuation of the long-term flexibility of an option (Beh et al., 2015a; Deng et al., 2013). Tools such as Real Options Analysis (Copeland and Antikarov, 2001; Jeuland and Whittington, 2014; Woodward et al., 2014), Adaptation Tipping Points (Kwadijk et al., 2010; Walker, et al., 2013a) and Dynamic Adaptive Policy Pathways (Haasnoot et al., 2013; Kwakkel et al., 2015) have been developed to achieve this. A combination design approach maximising both short-term flexibility and long-term robustness may yield the optimal strategies for future WRM adaptation planning, and is an area for further investigation.

8.2.5 Advanced water resource technology

The United Nations have reported that by 2025 approximately 1.8 billion people will live in regions that face "absolute water scarcity" due to climate change, population growth and the inadequacies of current water resource technology in physically or economically stressed regions (FAO, 2012). Continued innovation within water resource technology as well as management processes is essential if water supply is to be maintained in the growing number of water scarce regions on the planet.

Although not directly linked to the decision making method processes investigated in this thesis, an important aspect for consideration in future WRMPs is an improved optioneering investigation into alternative/advanced technologies when developing the pool of potential intervention options. During early water company optioneering phases a wide range of new resource options (and ways to reduce water consumption/losses) are considered; however, this range of diverse options is often swiftly reduced to a number of favoured, more cost-effective, interventions. This often overlooks potential options/technologies that may have high capital costs, or still be in an experimental phase, but could inherently increase the robustness and resilience of water supply to aspects such as severe climate change/variability.

For instance, desalination has long been a vital provider of potable water to communities where cheaper fresh surface or ground water alternatives are not available. The technology is known to be very energy intensive, clarifying its prevalence in energy rich nations, such as Australia, the US and many countries in the Middle East, and it is often installed as a last resort. Its typically high capital and operational costs meant it was infrequently selected in the optimal strategies identified in the case study work carried out in Chapter 5 (see Figure 5.4 in section 5.3.3). However, if this vital (climate change resilient) technology is to be utilised worldwide, especially in the most fresh water scarce developing nations then the energy consumption of the process needs to be significantly reduced, or ideally, be made energy neutral.

Several prototype energy neutral or renewable / low energy desalination concepts are under research including: forward osmosis models (Cath et al., 2006); direct or indirect solar desalination (Blanco Gálvez et al., 2009; Qiblawey and Banat, 2008; Qtaishat and Banat, 2013), i.e. utilising direct solar ray distillation or solar power (see Figures 8.3 and 8.4 respectively); magnetic nanoparticle membrane desalination (Zhao et al., 2013) and capacitive deionisation desalination (Suss et al., 2015), to name a few.

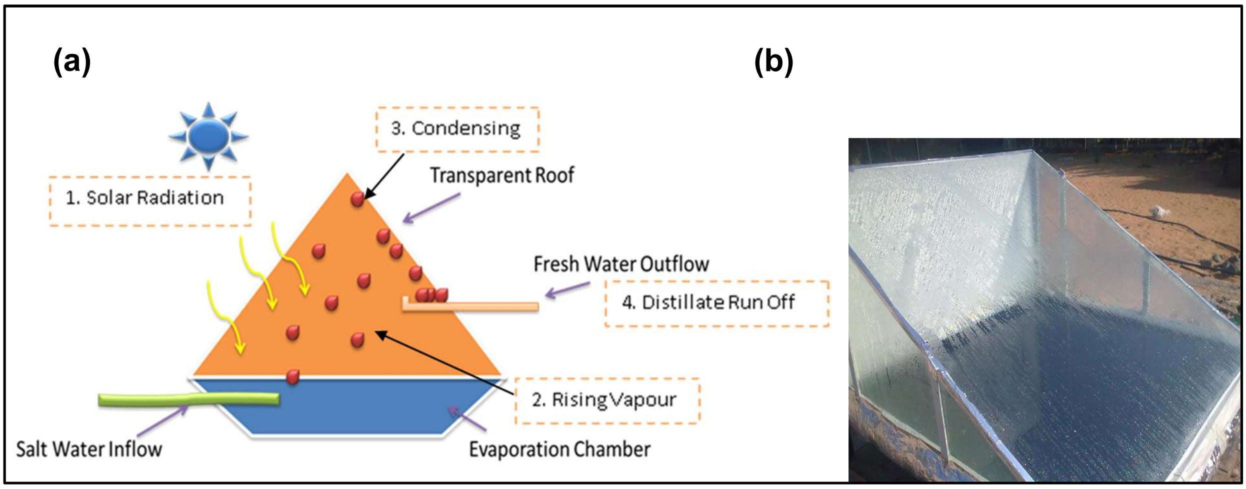

Figure 8.3: Examples of direct solar distillation desalination for developing nations: (a) concept drawing, (b) prototype module (ICWC, 2015)

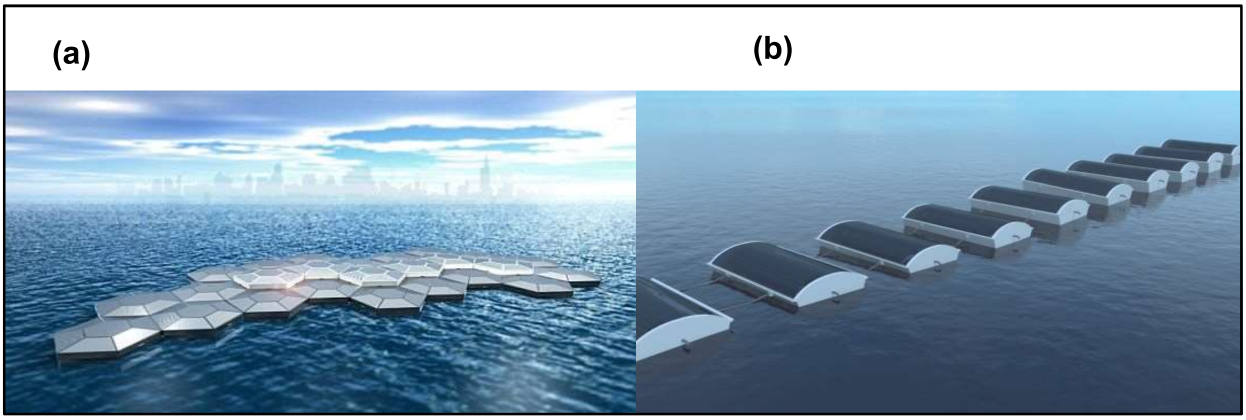

Figure 8.4: Examples of indirect solar desalination concepts ideas: (a) Aquahex design (Aquahex, 2013), (b) Solar Cucumber (Pauley, 2013)

Direct or indirect solar desalination is a particularly favourable concept given the common coupling of intensive sunlight and low rainfall in many water scarce regions around the planet. An advanced form of direct desalination has great potential for developing nations given its relatively low cost and zero energy requirements when utilising natural solar distillation (Figure 8.3); whereas indirect solar desalination (utilising a combination of renewable solar energy and low powered membrane treatment technology) is favourable for more developed nations which require a higher deployable output, especially in light of the steadily reducing costs of solar power.

Several alternative emerging technologies are under development, including forms of aquifer recharge (Dillon, 2005; Kurtzman et al., 2013; Lennon et al., 2014), water reuse and rainwater harvesting (Kalungu et al., 2015; Lebel, Fleskens et al., 2015), with particular regard being given to low or zero energy resource forms for developing nations (Kostiuk et al., 2015; Qaiser et al., 2013). However, the key message here is that water companies, both UK-based and international, must continue to innovate and expand the range of intervention/resource options considered for long-term planning. Future frameworks should include greater examination of alternative low-energy climate resilient options and ideally incentives given to endorse and encourage companies to trial technologies and plan low energy strategies that are sustainable and renewable.

8.2.6 Additional uncertainties and threats of the future

Climate change is increasing areas of water scarcity around the world, but it is also generating an increase in severe weather events and expanding the global regions suffering from desertification and at threat of rising sea-levels. These issues greatly increase the chance of large scale involuntary migration occurring (WEF, 2016), either under emergency conditions (e.g. a sudden severe weather disaster) or as a drawn out movement of people over time (e.g. abandoning water scarce areas or regions becoming inundated by sea-level rise). Mass involuntary migration of people is not currently a consideration within modern WRM planning approaches around the globe; however the impacts of such events could be devastating to both the groups relocating and the area taking in climate refugees. International regions near to areas at high risk of large scale migration need to begin factoring in these occurrences and assess how resilient their systems are to a sudden in-flux of migrants. Conversely, areas at threat to extreme weather, flooding and rising sea-levels also need to examine how resilient their water resource systems are to such occurrences and begin planning contingencies for the worst case scenarios. We are moving into a modern era of anthropogenic uncertainty and it is vital that the water resource systems of the world are prepared for the worst circumstances.

Newly proposed high-capital large-scale infrastructure can provide a significant supply addition to a water network; however, they intrinsically bring a security threat and place high dependency on individual large resources. Such resources could present a target for terrorist attack or increase the susceptibility of the system to extreme weather events should natural disasters impact on key resource locations or on the power assets that drive them. These ‘indirect’ uncertainties and their potential impacts on resources also need more consideration to ensure true robust modern day WRM adaptation planning is carried out.

8.3 Summary

The work carried out throughout this study has led to a range of specific conclusions, both qualitative and quantitative, in relation to specific methods and metrics for application to improve WRM adaptation planning under deep uncertainty. The purpose of this chapter was to consolidate those conclusions into a “minimum standard” list of aspects that should ideally be considered when approaching WRM adaptation problems under uncertainty in the future. It is recommended that future WRM frameworks should include or facilitate the following:

1. Define and use multiple objectives
2. Utilise optimisation algorithms
3. Incorporate complex simulation models into planning process
4. Employ improved uncertainty characterisation and assessment
5. Include an explicit robustness examination
6. Incorporate additional performance metrics
7. Increase the transparency of adaptation strategy assessments
8. Provide improved visualisations of trade-off examinations
9. Deliver a manageable step change from current practice
10. Include a more thorough optioneering investigation
11. Encourage more inter-sector cooperation and collaboration

Additional important planning aspects discussed that should undergo further consideration to enhance adaptation planning procedures and improve the overall robustness/resilience of future water resource systems include an examination of:

1. Multifunctional water resource options
2. Interconnection of resource networks
3. Collaborative planning and management
    a. with neighbouring water companies
    b. with other sectors
4. Flexible water resource options
5. Advanced water resource technology
6. Increased awareness and planning for additional uncertainties / system threats

Climate change uncertainty is now inherent in the modern world we live in but it has the advantage of stimulating research into alternative ways of providing water and sanitation. The scientific and engineering communities must embrace this challenge and take the threat of future uncertainties as an opportunity for robust and resilient innovation. A reform of the governance of national water resource systems may be the first adaptation step change required for many nations if new frameworks and approaches are to be successfully established, especially in developing nations more susceptible to the corruption of private companies (OECD, 2009). For many countries in the grip of privatisation it has long been argued by industry and investors that putting water in private hands translates into improvements in efficiency, service quality and management. However, with profit the primary objective of private companies, the idea of water as a human right arguably becomes a secondary concern. It is important to recall the conception that water supply is a fundamental human right and the robustness of its supply should not be marginalised in order to protect a profit margin. The availability of water over the next decade will be challenged in ways we have never seen. It is the single most important element, responsible for shaping human existence to date. It will continue to be so tomorrow and our ability to manage its uncertainties will define our future.

Chapter 9. Summary, Conclusions and Further Work

9.1 Introduction

This chapter provides a summary of the main findings and conclusions derived from each section of work presented in this thesis in relation to the research objectives laid out in Chapter 1, including overall project conclusions. It closes by describing several recommendations for further research.

9.2 Summary and conclusions

9.2.1 Objectives 1 and 2 – Review and qualitative comparison of DMMs for WRM under uncertainty

An extensive literature review of potential decision making methods for use in WRM planning was conducted leading to the selection of five predominant DMMs for a more in-depth qualitative comparison. The methods selected for examination included: Info-Gap decision theory (Y. Ben-Haim, 2006); Robust Optimisation (Ben-Tal et al., 2009); Robust Decision Making (Lempert and Groves, 2010); Decision-Scaling (Casey Brown, 2010) and Multi-Criteria Decision Analysis (Dorini et al., 2011), as well as discussion on several alternative/classical decision theories: Real Options Analysis (Jeuland and Whittington, 2014); Minimax Regret (Li et al., 2009); Laplace principle (Laplace, 1951) and Wald's Maximin theory (Wald, 1945). The methods were compared qualitatively using six assessment criteria: handling of planning objectives; handling of intervention strategies; uncertainty handling; selection mechanisms; computational requirements and output formats.

The comparison of methods indicated a number of key criteria/processes that would benefit from further quantitative assessment on real-world case studies. The review highlighted seven areas of key interest in particular that present contrasting theories of handling uncertainty in the WRM context which, at the same time, have had limited literature attention to date. In conclusion the seven comparative areas identified were as follows:

(a) A local vs global measures of robustness,

(b) Pre-specified vs optimisation-generated adaptation strategies,

(c) Top-down vs bottom-up assessment structures,

(d) Fixed vs fixed-adaptive vs flexible-adaptive strategy designs,

(e) Regret vs non-regret based assessment criteria,

(f) Singular optimal results vs Pareto optimal sets and

(g) Risk-based vs reliability and resilience based performance metrics.

The review also highlighted the concept of *Resilience* as a potential alternative primary performance metric and/or planning objective for water resource adaptation, which, to date, had yet to be clearly defined in WRM literature.

9.2.2 Objectives 3 and 4 – Quantitative comparison of DMMs for WRM under uncertainty on case studies

Following the qualitative review of methods, two DMMs were selected for further quantitative analysis of WRM under uncertainty on real-world case studies. The methods selected were Robust Optimisation and Info-Gap decision theory. These two methods were selected because they allowed an examination of contrasting local vs global measures of robustness as well as the effect of utilising pre-specified vs optimisation-generated intervention strategies.

A generic water resource software model was developed for implementing the subset of methods identified and capable of interacting with a wide range of water resource networks/system models. The simulation model was developed to replicate, using a daily or monthly time step, the supply and demand balance of a regional water supply system over a pre-established time horizon. During software development it proved difficult to incorporate the traditional Info-Gap 'stability radius' method for analysing robustness/sensitivity to uncertainty whilst employing discrete scenario projections that were not monotonically increasing. Therefore, a novel area-based method for IG robustness modelling of uncertain future supply and demand scenarios was developed.

Two case studies were then developed recreating the water resource networks of two real-life UK based resource zones. The case studies selected were:

- Southern Water's Sussex North resource zone
- Bristol Water's Water resource zone

The case study models were set up to accurately recreate the existing water resource networks and a full range of potential intervention options (for the formation of adaptation strategies) and future scenarios of supply and demand were derived for each region for testing of the DMM software and dynamic water resource simulation model developed during objective 3. The case studies were of varying complexity and utilised alternative performance metrics, planning horizon lengths and numbers of supply and demand scenarios. The results obtained across the two case studies lead to the following key conclusions:

1. Robust Optimisation, with its global robustness analysis, appears the more favourable DMM for the WRM problems examined here. Its simpler computational set-up and operation allowed an easier examination of future scenarios when utilising an ensemble of *prospective* transient flow projections. The RO analysis also led to the identification of lower costing adaptation strategies across both case studies for all given levels of desired robustness. Info-Gap had a more complex set-up and the localised mapping methodology proved problematic when applied to a wide range of discrete scenario projections that were extremely variable and not monotonically increasing.

2. The novel area-based robustness search technique developed for the IG method application improved on previous scenario mapping practices by allowing more scenario combinations to be analysed and allowing the robustness search to continue until all scenario expansion routes ended in system failure.

3. The location of the starting points of the IG analysis did not significantly alter the Pareto strategy results obtained in the simpler case study (Sussex North) but did in the more complex problem (Bristol Water). The Bristol water study utilised a larger region of uncertainty signifying that the starting location of the IG analysis is more impacting on outputs as the uncertainty region increases, highlighting the importance of carefully selecting the initial start point.

4. The IG performance could be improved by switching to using uncertainty variables instead of using transient flow projections; however, the

purpose here was to examine how the DMMs handle complex ‘scenario’ assessments in practice, as approaches that characterise uncertainty via scenario development/assessment are being increasingly regarded as the next step for evaluating complex systems to deep uncertainties (Maier et al., 2016; Moss et al., 2010).

5. In assessment of pre-specified vs optimisation-generated adaptation strategies (investigative area (b) from section 9.2.1), it was discovered that Info-Gap required optimisation based automatic generation of strategies as the case studies became more complex. The larger pool of potential intervention options made it problematic to reliably pre-specify strategies for testing, reinforcing the suitability of a form of Robust Optimisation for WRM adaptation planning.

6. Both DMMs could produce a Pareto optimal set of adaptation strategies (either formed automatically or following the ranking of results), which ultimately allows a visualisation of trade-offs across the objectives before final strategy selection is carried out. This improves on current UK engineering practice, which typically pre-specifies a linear projection of future supply and demand and then optimises to derive a single optimal adaptation strategy solution. Single objective (least cost) optimisation, as in the current practice EBSD method, effectively determines only a single point on the Pareto fronts identified by the DMMs here, and so does not provide any trade-off comparisons.

7. A fixed strategy design (i.e. unchanging the set sequence of interventions in the strategies examined from input to output) suffers from the same computational issues experience when pre-specifying a selection of strategies when system complexity, larger data sets and a larger pool of potential intervention options are used. A fixed-adaptive design (either manually altering strategy designs as vulnerabilities are detected (as with RDM), or mutating strategy designs within optimisation processes (as done here with RO)) proves more beneficial at testing multiple strategy design configurations in a much more computational acceptable time frame. Examining every form of potential fixed strategy design when millions of potential combinations exist is not practical.

8. The comparison between using a risk-based metric and an individual criterion (reliability) based metric (investigative area (g) in section 9.2.1) is difficult to directly analyse across the two case studies; although, from an immediate practical point of view it is arguably more informative to use a reliability criterion to measure the performance of the water system as it provides clearer insight into the relative frequency of water deficits detected over the planning horizon. The risk-based metric identified strategies that could maintain a given level of risk over a given planning horizon; however, the calculation of risk is far less transparent when you amalgamate both likelihood and severity into a single parameter and it remains unclear just *how many* water deficits are occurring and at *what magnitude*. In order to better compare the effect of altering the performance metrics utilised it is recommended that a more complete investigation into potential indicators be conducted, which explore individual criterions of performance; such as examining the frequency, duration and magnitude of water deficits (Hashimoto et al., 1982) and how this can better inform decision makers on the performance of the water system.

9. In comparison with the SW and BW WRMPs 2015-40 proposed plans it was concluded that quantifying the robustness explicitly (as opposed to indirectly, via headroom and level of service failure) and using this and costs as drivers to identify solutions, is likely to result in more robust and less costly plans when compared to a more conventional approach used in current UK engineering practice. However it was observed, at least in the case studies analysed here, that increasing the current 25 year planning horizon to a 50 year analysis did not significantly influence the intervention options selected over the initial 25 years of the plan.

10. The variation in the Pareto strategies derived highlight how the current industry standard for water supply system adaptation planning could benefit by applying a wider range of decision methodologies and assessment tools (especially those that quantify a level of system 'robustness') as well as a more encompassing investigation into potential future uncertainties and alternative methods for scenario generation.

9.2.3 Objectives 5 and 6 – Performance metric investigation and development of novel resilience-based methodology

The findings from the two case studies concluded that more research should be conducted into the comparison and evaluation of performance metrics/indicators for WRM adaptation planning. Therefore a more detailed investigation to explore and analyse a range of applicable performance metrics for WRM adaptation planning was conducted, specifically to derive the optimal metric that could be used to define system resilience. Ten different metrics were selected for an in-depth analysis that exhibited desirable performance metric characteristics (see Table 6.1). The analysis included an examination of metric sensitivity and correlation, as well as a detailed examination of the behaviour of water deficit periods. This led to a range of recommendations for the selection of an appropriate resilience-based performance metric. In general it was found that:

1. Multiple metrics covering different aspects of resilience are recommended for providing additional water deficit information, then is presently utilised in current practice.

2. The "duration of longest water deficit period" metric stood out as the most all-encompassing and informative performance metric followed closely by the "water deficit of greatest magnitude recorded" metric. However, the correlation analysis demonstrated a high linearity between the two metrics and therefore considering just a single metric may prove sufficient to evaluate the resilience of a water resource system. A duration based metric would be a more logical assessment metric to use of the two types, as it is the duration of temporary water restrictions that most impact on customers and supply, whereas the magnitude of water deficit events is of less direct concern to customers and water companies so long as the magnitude is maintained within acceptable threshold levels.

3. Frequency type resilience metrics cover important aspects/information, but should not be used on their own as they do not capture the size of 'impact' on the system and provide limited information on water deficit periods, so should not be used on their own.

4. Aggregated type resilience metrics are fairly sensitive to different adaptation strategies and supply/demand scenarios but there is also a considerable uncertainty in their calculation due to their nature (i.e. is it a single big or several small deficit periods occurring to give the final values) making it harder to clarify exact adaptation strategy and system performance.

5. Magnitude type resilience metrics are highly sensitive and provide useful information, especially in terms of proximity to critical threshold levels; however, they do not provide a full picture of deficit events/periods.

6. Duration type resilience metrics are also highly sensitive with "the duration of longest water deficit period" providing the most detailed and informative picture of a deficit event. It is also the metric that exhibits the highest correlation to all other metrics. Splitting the duration of a water deficit period into the time to max peak deficit and time to recover from max peak deficit (as suggested in Linkov et al. (2014)) provides more detailed water deficit period information, but the relative performance of each aspect tends to be highly variable when assessed across multiple scenarios of future supply and demand, reducing the clarity of each as a consistent measure of performance.

A new resilience driven methodology for WRM planning was developed and tested utilising the optimal resilience-based performance metric derived. The method optimised for resilience and cost for a given target level of robustness utilising the dynamic water resource simulation model and was applied to the more complex Bristol Water case study. This new approach provided a 3D trade-off surface of Pareto-optimal solutions providing decision makers with a better picture of what system performance benefits different planning strategies can achieve. The method utilised a global measure of robustness and optimisation-generated adaptation strategies. This new methodology was compared with the current UK planning practice of identifying a single least cost strategy subject to maintaining a target level of reliability (frequency of deficits). It was found that:

1. Optimising for a single objective in the current practice methodology yields only a single solution that is highly dependent on the initial target

robustness (headroom) and target reliability selected and does not provide alternative solutions that may achieve benefits for small trade-offs.

2. The strategy solution derived using the current practice methodology produced in the real-life case study analysed a less resilient system than the similar costing solutions identified using the proposed resilience driven methodology. Whereas the resilience driven strategies were less reliable (although not by much), suggesting that trade-off exists between the two.

3. In order to better explore the trade-offs that may be gained by considering both resilience and reliability, it is recommended that the resilience driven methodology is further developed with the inclusion of a reliability criteria as an additional objective or constraint in the approach presented here.

4. The resilience driven methodology yielded planning strategies which space interventions more evenly across the planning horizon when compared to the current practice (reliability driven) strategy solution, which scheduled more lower cost interventions earlier in the planning horizon. This suggests that, at least in the case study analysed here, more low cost interventions early in the planning horizon achieve higher system reliability whereas regular intervention options spread over the planning horizon achieve higher system resilience when planning to an uncertain future. Examination of both metrics is recommended if optimisation of the additional system attribute (resilience) is desired in future UK practice.

5. The resilience-based methodology improves on key industry planning issues by increasing the transparency of adaptation strategy assessment processes and improving the information available to decision makers. The method also improves on the economic cost appraisal of water restriction periods, as a duration of deficit is more easily quantifiable than a frequency-based approach. The resilience methodology created a 3D surface of Pareto-optimal solutions providing decision makers with a more complete trade-off picture of what different planning strategies can

achieve in terms of system performance benefits and related costs thus enabling them to make better informed decisions.

9.2.4 Objectives 7 and 8 – Future WRM framework improvements and overall conclusions

Key research findings and priority items for future adaptation planning methods and approaches were discussed in Chapter 8. Some overall key conclusions derived from across this research are as follows:

1. All DMMs have certain strengths and weaknesses depending on their application and user requirements. Employing a plurality of approaches to an adaptation problem under deep uncertainty may be the answer, as the decision maker can take advantage of each DMMs unique features and identify strategies that repeatedly perform well.

2. The ability to overlap method processes have been highlighted, i.e. the ability to apply optimisation to all methodologies and utilise alternative scenario generation techniques. This suggests that the development of an optimal framework for complex WRM planning under uncertainty may involve one that will utilise (perhaps hybridise) features from a range of DMMs with the aim to exploit advantages and minimise disadvantages of existing methods and would help simplify a range of complex mathematical decision theories into a practical set of procedures.

3. The DMM ultimately selected for advancing WRM adaptation planning will inevitably have trade-offs in performance with alternative approaches. For instance, if a method seeks global robustness to uncertainty across a large range of future scenarios, uses multi-objective evaluation or automatically generated intervention strategies the trade-off is that the DMM will be more computationally demanding, require expert knowledge or specialist software codes. Whereas, if the method analyses fewer future scenarios (examining a localised radius of uncertainty), uses single-objective evaluation or utilises pre-specified intervention strategies the DMM will be less computational demanding and simpler to implement.

4. The key approach is striking a balance between planning aspects while satisfying all stakeholders involved but ensuring a justifiable level of system performance is established.

The ideal future WRM planning under uncertainty framework should include or facilitate the following:

1. Define and use multiple objectives
2. Utilise optimisation algorithms
3. Incorporate complex simulation models into planning process
4. Employ improved uncertainty characterisation and assessment
5. Include an explicit robustness examination
6. Incorporate additional performance metrics
7. Increase the transparency of adaptation strategy assessments
8. Provide improved visualisations of trade-off examinations
9. Deliver a manageable step change from current practice
10. Include a more thorough optioneering investigation
11. Encourage more inter-sector cooperation and collaboration

Additional important planning aspects discussed that should undergo further consideration to enhance adaptation planning procedures and improve the overall robustness/resilience of future water resource systems included an examination of:

1. Multifunctional water resource options
2. Interconnection of resource networks
3. Collaborative planning and management
    a. with neighbouring water companies
    b. with other sectors
4. Flexible water resource options
5. Advanced water resource technology
6. Increased awareness and planning for additional uncertainties / system threats

9.3 Summary of novel research contributions

This research has contributed to existing WRM knowledge in several distinct ways. It qualitatively evaluated and then quantitatively applied and tested a range of decision making methods, known to originate from economics and game theory, to a new domain of water resources management. This developed new knowledge and understanding as to the specific pros and cons of the different approaches and how they can improve on current water resources adaptation planning and practice.

During detailed quantitative analysis of two selected decision making methods several further contributions to knowledge were made including: the development of a dynamic water resources simulation model that can be customised to model a range of water resources networks and DMMs; the creation of a novel area-based info-gap robustness mapping model customising the original methodology to allow utilisation of discrete non-linear future scenarios of supply and demand in the analysis process; and the development of a new rolling flow factor method to produce a wider range of varied and more comprehensively perturbed transient supply scenarios.

Additionally this study developed and reviewed a range of new potential performance metrics that could be used to quantitatively assess system resilience to help answer the water industries question of how best to build in more resilience in future water resources adaptation planning. This led to the creation and verification of a novel resilience-based methodology for optimal water resources planning.

Finally, the research closed with discussion on the potential future of adaptation planning in the water industry and the development of a list of recommended "minimum standards" for an ideal future procedural framework. These findings could have an impact on new water resource planning legislation and policy and would be of interest to a wide range of regulatory bodies, environmental agencies and water companies with the agenda of improving system resilience to a future of rising deep uncertainties.

9.4 Recommendations for further research

The application of decision making methods to solve water related adaptation problems under deep uncertainty is a growing scientific field with many facets that could be further explored. The recommendations for further research on the topics presented and discussed in this thesis are as follows:

- The flexibility/adaptability of solutions is an aspect not explored within the approaches presented here. In practice evaluating only fixed rather than adaptable strategies limits the range of potential long-term trade-offs explored. This limitation can be overcome by combining these DMMs with modern approaches such as Real Options analysis (Jeuland and Whittington, 2014), Adaptive Pathways (Kwakkel et al., 2014) or Adaptive Multi-Objective Optimal Sequencing (Beh et al., 2015a). A combination design approach optimising for both short-term flexibility and long-term robustness may yield the optimal strategies for future WRM adaptation planning, and is an area for further investigation.

- Further case study assessments would also better reveal the strengths and weaknesses of the various methods examined here. Efforts were made to make the simulation models utilised in the case study assessments as real to life as possible; however, it would be beneficial to test the methods described here in direct combination with a more complex resource model package, such as a water company MISER model or AQUATOR platform, to see how easily the methods can be incorporated into an actual multi-nodal company network simulation model.

- The water resources simulation model utilised in the case studies (Chapters 5 and 7), although dynamically able to model the daily or monthly supply and demand balance of a complex water system over a long-term time horizon, could be further improved to incorporate additional dynamic and flexible system aspects. This could include conditions such as the ability to switch resource options on and off at specific points in the time horizon to reduce operational costs or to reserve water, or to examine the effect of outage (i.e. due to the flooding of assets etc.). The analysis also assumed the performance of each intervention option selected and applied to the model was independent of future changes (i.e. constant DO values were used). However, the water yield from several of the new resource options will likely be affected by changes in the climate system and are therefore themselves dynamically linked to the deep uncertainties within the system. For example, option R4 from the Bristol Water case study (the new reservoir at Cheddar) is assumed to yield 16.3 ML/d under all future climate conditions, which is not likely to be the case. Flooding events are also expected to increase in frequency in the future providing further risk of outage of individual resources/assets adding further uncertainty to the supply issues discussed here. The models developed here could be further improved if the iterative, dynamic approach used for characterising future uncertainties in the existing water resources were applied to all climate vulnerable intervention options also.

- It is expected that further research within this area will ultimately lead to the development of a novel framework for complex WRM planning under uncertainty for real-world application to the UK water sector to update existing outdated practices. This final updated framework may utilise (perhaps hybridise) features from a range of DMMs with the aim to exploit advantages and minimise disadvantages of existing methods (e.g. using optimisation to select and test more strategy combinations, combined with new vulnerability map or scenario discovery methodologies (e.g. Singh et al., 2014) with objectives set up to examine the trade-offs between robust and flexible solutions across multiple-objectives).

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