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Planning water resource systems under uncertainty

A thesis submitted to the University of London for the degree of Doctor of Philosophy

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Declaration

I, *Evgenii Matrosov*, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

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Abstract

Stationarity assumptions of linked human-water systems are frequently invalid given the difficult-to-predict changes affecting such systems. Population growth and development is fuelling rising water demand whilst in some parts of the world water supply is likely to decrease as a result of a changing climate. A combination of infrastructure expansion and demand management will be necessary to maintain the water supply/demand balance. The inherent uncertainty of future conditions is problematic when choosing a strategy to upgrade system capacity. Additionally, changing stakeholder priorities mean multi-criteria planning methods are increasingly relevant. Various modelling-assisted approaches are available to help the water supply planning process. This thesis investigates three state-of-the-art multi-criteria water source systems planning approaches. The first two approaches seek robust rather than optimal solutions; they both use scenario simulation to test the system plans under different plausible versions of the future. Under Robust Decision Making (RDM) alternative strategies are simulated under a wide range of plausible future scenarios and regret analysis is used to select an initial preferred strategy. Statistical cluster analysis identifies causes of system failure enabling further plan improvement. Info-Gap Decision Theory tests the proposed strategies under plausible conditions that progressively deviate from the expected future scenario. Decision makers then use robustness plots to determine how much uncertain parameters can deviate from their expected value before the strategies fail. The third approach links a water resource management simulator and a many-objective evolutionary search algorithm to reveal key trade-offs between performance objectives. The analysis shows that many-objective evolutionary optimisation coupled with state-of-the art visual analytics helps planners assess the best (approximately Pareto-optimal) plans and their inherent trade-offs. The alternative plans are evaluated using performance measures that minimise costs and energy use whilst maximising engineering and environmental performance criteria subject to basic supply reliability constraints set by regulators. The analyses show that RDM and Info-Gap are computationally burdensome but are able to consider a small number of candidate solutions in detail uncovering the solutions' vulnerabilities in the face of uncertainty in future conditions while the multi-objective optimisation approach is able to consider many more possible portfolios and allow decision makers to visualize the trade-offs between performance metrics.

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Additional contributions

The Info-Gap Decision Theory study (Chapter 5) was performed jointly by the author of this thesis and Ashely Woods. The author created the model of the system and coded IRAS-2010 to perform the Info-gap simulations. The formulation was done jointly. The Info-gap simulations and results analysis was performed by Ashley Woods. Ashley also contributed Figure 2.2, Figure 5.1 and Figure 5.2.

Silvia Padula performed the Economics of Supply and Demand study (Appendix). She also contributed Figure 4.10.

The Multi-Objective Evolutionary Optimisation Study was done jointly with Ivana Huskova. The author adapted the IRAS-2010 code and the Thames system model, formulated the study while Ivana Huskova coded the C++ wrapper code and performed the optimisation runs. Results analysis was performed by the author.

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List of Acronyms

ALC	Active Leakage Control
CAPEX	Capital Costs
CENT	Central Water Resource Zone
CT	Columbus Transfer
MET	Compulsory Metering
CDF	Cumulative Distribution Function
DSS	Decision Support System
DRS	Deepham Reuse Scheme
DM	Demand Management
DO	Deployable Output
DESAL	Desalination Plant
DP	Dynamic Programming
EBSD	Economics Of Balancing Supply And Demand
EA	Environment Agency
ε-NSGAII	Epsilon-Dominance Non-dominated Sorted Genetic Algorithm II
ESW	Essex And Suffolk Water
FOPEX	Fixed Operating Costs
GLUE	Generalized Likelihood Uncertainty
GCM	Global Circulation Model
Info-Gap	Info-Gap Decision Theory
IP	Infrastructure Portfolio
IWRM	Integrated Water Resource Management
LOS	Level Of Service
LP	Linear Programming
LAS	London Aggregate Storage
LDN	London Water Resource Zone
LRD	Long Reach Desalination
LTCD	Lower Thames Control Diagram
MAINS	Mains Replacement
MILP	Mixed Integer Linear Programming
MOEA	Multi-Objective Evolutionary Optimisation
NRFA	National River Flow Archive
NSDO	New Supply or Demand Management Option

NLARS	North London Artificial Recharge Scheme
NT	Nothern Transfer
PRIM	Patient Rule Induction Method
PDM	Probability Distributed Model
PDF	Probability Distribution Function
L	Restriction Level
RST	River Severn Transfer
RDM	Robust Decision Making
RO	Robust Optimisation
SETA	Seasonal Tariffs
SI	Shortage Index
IRAS-2010	Source Interactive River-Aquifer Simulation-2010
SLARS	South London Artificial Recharge Scheme
SOUTH	Southern Water Resource Zone
SRES	Special Report On Emissions Scenarios
SD	Stability Degree
SP	Stochastic Programming
SDO	Supply or Demand Management Option
SWOX	Swindon And Oxford Resource Zone
TWUL	Thames Water Utilities Limited
UKCP09	United Kingdom Climate Projections 2009
UTR	Upper Thames Reservoir
VAREX	Variable Operating Costs
VTVW	Veolia Three Valleys Water
WAFU	Water Available For Use
EFI	Water Efficiency Improvements
WRMP	Water Resource Management Plan
WRZ	Water Resource Zone
WTW	Water Treatment Works
WBGW	West Berkshire Ground Water Scheme

1 Introduction

1.1 General background

Nearly 1.2 billion people live in areas of physical water scarcity whilst another 500 million might soon face this situation (Earthscan, 2007). An additional 1.6 billion people live in countries that lack the necessary infrastructure to abstract water from natural water sources (Earthscan, 2007). Water stress is likely to increase in certain areas as population and economic growth contribute to increasing water demand (Alcamo et al., 2003). Exacerbating the problem, climate change is likely to create drier conditions in some parts of the world (Milly et al., 2008).

Decision-makers are tasked with designing appropriate water supply plans that preserve the supply/demand balance at low economic cost and with minimal environmental and social implications. The large capital cost of new infrastructure combined with the risk of social and environmental costs of inappropriate planning decisions imply the stakes are high. Uncertainty in future conditions poses challenges to supply-demand planning. Agricultural, industrial and domestic demand growth is difficult to forecast, can be influenced by climate change (IPCC, 2013) and is subject to uncertainty (Alcamo et al., 2003; Browne et al., 2013). Predictions on the effect of climate change on water availability in many areas vary considerably. For example, the UK Climate Projections (UKCP09) (Murphy et al., 2009) predict that by the 2050s summer temperatures may increase between 1.3 °C - 4.6 °C in South-East England whilst winter temperatures would see an increase of 1.1 °C - 3.4 °C under a medium range CO_2 emissions scenario. This is predicted to result in a 2% - 36% increase in winter precipitation but up to a 7% - 40% decrease in summer precipitation. These changes would most likely result in substantially reduced summer river flows and reduced groundwater recharge rates. These figures were calculated using a medium range emissions scenario. Murphy et al. (2009) also considered low and high emissions scenarios which led to different ranges of predictions. Even when only considering one emissions scenario the range of the effects of climate change is greatly uncertain.

Water resource systems affect a wide range of stakeholders including, but not limited to, the public, farmers, national governments, water and energy companies, regulators including environmental protection agencies. Different stakeholders have varying and sometimes conflicting interests. There are inherent trade-offs between the economic costs, engineering performance and the societal and environmental impacts of engineered water systems. Initiatives such as

Integrated Water Resource Management (Agarwal et al., 2000) and the European Water Framework Directive are moving planning away from the top-down planning approach that dominated water resources planning in the last century (Castelletti and Soncini-Sessa, 2006). These initiatives promote a bottom-up planning approach by actively including interested stakeholders in the planning process. With a bottom-up approach stakeholder interests become integrated in the planning process.

1.2 Research problem and objectives

Water resource planning has long been performed with classical optimisation algorithms such as mathematical programming and dynamic programming (Loucks et al., 1981; Loucks and van Beek, 2005; Mays, 2005; Revelle, 1999). These methods often employ simplified and aggregated system models and have difficulties representing non-linearities. Often minimising economic costs is the sole objective with other non-commensurable performance criteria being translated into costs. In reality, the performance of water systems can be measured with multiple performance criteria that often have inherent trade-offs between each other (e.g. cost vs reliability). These trade-offs are masked when these different performance metrics are aggregated into the cost objectives.

Policies promoting bottom-up planning such as Integrated Water Resource Management (IWRM) are gaining acceptance resulting in stakeholders from diverse backgrounds participating in the planning process. These stakeholders have different and sometimes conflicting interests and priorities. The ability to identify and visualise the trade-offs of proposed water plans would facilitate the discussion between stakeholders and decision makers.

In addition to being uni-objective, classical optimisation-based capacity expansion methods grapple with cases where planning occurs under conditions of deep or severe uncertainty, where the statistical distributions of future conditions and events are poorly known and thus poorly quantifiable (more formally defined in Section 2.5.1). Systems that are optimal for a single expected future may not perform well if the actual realised future deviates from the conditions for which the system was optimised. Uncertainty can be taken into account by using stochastic optimisation. However, this method operates under the assumption that the probability distributions of the unknown variables is known or can be estimated, and that it is static. With 'deep' uncertainties such as the effects of climate change on future hydrology this assumption may no longer be valid. Indeed, predictions on the effects of climate change vary widely and often different climate models produce different results (Meehl et al., 2007). Water resource plans that are optimal for one expected future (or a set of futures derived from known probability distributions) may not perform well if the actual realised future deviates from the conditions for which the system was optimised.

Uncertainty in future conditions and changing stakeholder priorities are imposing a rethink of the current planning water supply practice. Indeed, the current planning method in England and Wales is under-review (Hall et al., 2011b). There is currently no consensus on which method, or methods, are fit to replace the current one. What planning methods can be used alone, or in conjunction with current methods, to develop water resource system plans that take into account the 'deep' uncertainty of future conditions, and explicitly consider the varying stakeholder interests?

The overarching aim of this thesis is to investigate potential state-of-the art methods which could replace the current water resource system planning framework in England and Wales. A new planning framework would be able to quantify water resource system performance in multiple metrics in order to take into account the range of stakeholder preferences. In order to accommodate this requirement, the first objective of this thesis is to develop a computationally efficient water resource system simulator that can be used with potential planning frameworks and that can simulate the system with fidelity and output multiple system performance metrics. The second objective is to investigate two state-of-art decision making frameworks (Robust Decision Making and Info-Gap Decision Theory) that can aid planners in finding plans that are robust to the 'deep' uncertainty of future conditions (i.e. plans that can perform well over a wide-range of possible future conditions). The third objective is to investigate a method that links a simulation model with a multi-objective evolutionary optimisation algorithm to search through the many proposed system infrastructure and demand management expansion options and produce multi-dimensional trade-off surfaces composed of the best system plans allowing stakeholders to visualise the inherent trade-offs between these multiple performance metrics. These planning methods are investigated by applying them to a real-world case-study system – the Thames water supply system.

1.3 Outline of the thesis

In the next chapter a literature review of water resource systems, how they are modelled and how their performance is quantified is presented. This is followed by a review of the current water resource system planning practices with an emphasis on the England and Wales context. The literature review then focuses on state-of-the-art planning frameworks. The concept of 'deep' uncertainty is introduced and then two scenario-based planning methods (Robust Decision Making and Info-Gap Decision Theory) that take into account 'deep' uncertainty and multi-criteria performance are reviewed. A third approach that links multi-objective evolutionary optimisation with simulation to explicitly consider the inherent multi-criteria nature of the water resource planning problem is then presented. This method allows decision makers to visualise the trade-offs between the multiple performance criteria.

Chapter 3 of this thesis presents the open-source Interactive River-Aquifer Simulation-2010 (IRAS-2010), a generalised water resource system simulator used in all three approach applications. IRAS-2010 is a new release of IRAS previously released by Cornell University in 1995. Given hydrological inflows, evaporation rates, water allocation rules, reservoir release rules, consumptive water demands and minimum environmental flows, IRAS-2010 estimates flows, surface water and groundwater storage, water use, energy use, and operating costs throughout the water resource network at each user-defined time-step. An IRAS-2010 model of London's conjunctive use water resource system that satisfactorily emulates a more sophisticated model currently used by regulators is then presented. IRAS-2010's fast run times make it appropriate for workshop settings and advanced water resource planning methods that require many model evaluations while its detail and ability to produce multiple performance measures make it suitable for multi-criteria planning studies. This chapter also introduces the Thames-basin. A Thames-basin planning problem is used as a case-study throughout this thesis. IRAS-2010 was published in *Environmental Modelling and Software*.

In Chapter 4 this thesis contributes two real-world applications of the Robust Decision Making (RDM) framework to water resources systems planning. In conditions of deep uncertainty planners may seek robust, rather than optimal plans. A robust solution is one that performs satisfactorily well in a wide range of conditions, rather than optimally in one or a few. Predictive system simulation models are typically run under different scenarios to evaluate the performance of future plans under different uncertain conditions. Robust Decision Making (RDM) provides a structured approach to planning complex systems under such ‘deep’ uncertainty RDM uses scenario simulation and regret analysis to develop robust plans. RDM samples a wide range of dire, benign and opportune futures and offers a holistic assessment of the performance of different options. RDM identifies through ‘scenario discovery’ which combinations of uncertain future stresses lead to system vulnerabilities. RDM is used to develop water resource management portfolios for the Thames basin water resource system under conditions of uncertainty in future hydrology, demand and energy prices for 2035. The first application includes only supply options whilst the second includes both supply options and demand management measures. The supply-only application has been published in the *Journal of Hydrology* whilst the supply and demand option application was published in *Water Resources Management*.

In Chapter 5 the Thames basin infrastructure planning problem is solved with Info-Gap Decision Theory. Like RDM Info-Gap helps decision makers find robust solutions. Info-gap efficiently charts system performance with robustness and opportuneness plots summarising system performance for different plans under the most dire and favourable sets of future conditions. Results show how Info-gap and RDM produce broadly similar results but provide complementary decision relevant information to water planners.

In Chapter 6 the IRAS-2010 water resource management simulator is linked to a many-objective evolutionary algorithm to reveal the key trade-offs inherent in planning the future Thames water resource system. The analysis shows how many-objective evolutionary optimisation coupled with state-of-the art visual analytics can help planners discover the best plans and their inherent trade-offs. The many-objective visual analytics demonstrated in this study reveal that classical least-cost, reliability constrained formulations could bias decisions away from higher performing plans whose benefits only become apparent with the consideration of a broader array of planning objectives. This work has been submitted to the *Journal of Hydrology*.

Finally, Chapter 7 gives a conclusion of the thesis and identifies future work that may be continued.

2 Literature of water resource systems planning

2.1 Water resource systems

Water resource systems include natural components such as lakes, river and stream reaches, wetlands and aquifers and engineered components such as reservoir systems, water allocation and diversion sites, water consumption sites, irrigation canals and hydropower and pumping stations. These lists are not exhaustive as real world systems are complex. System components interact with each other and the surrounding environment and can be influenced and governed by human policies and decisions. Challenges arise from interactions between different human activities, their interaction with and impacts on natural systems and the reciprocal responses of the natural systems back onto human activities (Salewicz and Nakayama, 2004).

Water resource models have been aiding decision makers, researchers and other interested parties in water resource planning since the 1950s (Maass et al., 1962). These models attempt to predict flows and storages of water in real world systems. They are used to determine how to allocate water to different uses and users; minimise the risks and consequences of adverse conditions such as droughts and flooding; optimise the cost, energy and land use in water management and minimise the impact that these actions have on the environment (Wurbs, 1993). They can be used to determine the effectiveness of management policies and decisions. Water resource system models can be divided into two categories: procedural simulation models that incorporate user defined operational rules and policies and models that use optimisation to simulate the flow of water throughout the network at each time step.

Since each approach has advantages and limitations, the institutional and water management context often determines which modelling type is most suitable for a particular application. For example a model seeking to predict water trading will benefit from an optimisation engine, whereas rule-based models are well-suited for modelling actual system operating procedures (e.g. reservoir release tables) and predicting their performance under certain conditions.

2.1.1 Rule-based simulation models

Rule-based models use procedural or object-oriented computer code where programming instructions sequentially define how water is managed using for example “if then else” statements and iterative instructions (‘loops’). The system behaves predictably according to the model input data (such as inflows and demand levels) and as defined by their operating policies. Iterative solution procedures are used to represent the interconnections between water requirements and management rules at different locations, often moving from upstream to downstream to route flows and track storage throughout the system. Such 'ad hoc' algorithms are challenging to build but have the potential to reproduce management mechanisms with high fidelity (Loucks and van Beek, 2006).

Simulation models can be run multiple times to determine how a system would perform under alternative operating policies or uncertain parameters or inputs. Alternative policies can include changing variables such as system inflows, demand levels, discharge rates or allocation rules and comparing the performance of the system in the subsequent model runs (Rani and Moreira, 2009).

Simulation models are often employed in decision support systems (DSS) (Lautenbach et al., 2009) and have also been coupled to optimisation models in non-linear economic optimisation studies (Ahrends et al., 2008). Examples of generalised rule-based models available with a user-interfaces include RIBASIM (WL Deflt Hydraulics, 2004), WRAP (Wurbs, 2005b), HEC-ResSim (Klipsch and Hurst, 2007), WaterWare (Cetinkaya et al., 2008), AQUATOR (Oxford Scientific Software, 2008) and WARGI-SIM (Sechi and Sulis, 2009). Table 1.1 summarises selected defining features of a representative set of rule-based simulators including whether they allow scripting and whether their time-steps are fixed or user-selected. Scripting allows customizing actions of particular nodes or links in a network using a generalised programming language rather than modifying source code. Scripting increases flexibility but requires more skilful users.

Table 1.1 Selected benefits and limitations of a representative group of rule-based water resource simulation modelling systems.

Model	Selected characteristic features
IRAS-2010	Free and open-source; Computationally efficient; Multi-reservoir operating rules; Flow routing; Time-step is user-selected between 1 and 365 days; Fortran code can be compiled on Windows and Unix machines and customized.
AQUATOR	Flexible generalised scripting at nodes and links using the VBA language; Conjunctive surface and groundwater use simulation; Optimisation of water allocation based on supply and cost; data import facilities; Time-step is daily.
RIBASIM	Wide variety of features (lay-out, demand and control nodes) and several link types; Links to DELWAQ water quality model and HYMOS hydrological model; Geographic interface; Number of performance metrics; Various hydrological flow routing methods; Many international case-studies; Time-step is user-selected between monthly and daily.
WRAP	Represents priority-based water allocation; Calculates supply reliability performance measures; Facilities to model allocation based on water rights permits; No editing or graphics capabilities, text input files; Time-step is user-selected between monthly and daily.
HEC-ResSim	Includes generalised scripting using the Jython language for reservoir rules allowing complex rules including flood control operations; Operational focus rather than long-term planning; Multiple routing methods; Geographic interface; Incorporates time-series generated by sister hydrologic model HEC-HMS; Variety of visual output and plots for results analysis; Public domain (free); Time-step is user-selected between daily and 15-mimute intervals.
WaterWare	Object-oriented software architecture; Supports integration of GIS; Includes native rainfall runoff, water quality, and irrigation demand models; Web-interface with user-management which allows running models on servers and clusters; Link to heuristic optimisation procedures for calibration and management; Time-step is daily.
WARGI-SIM	Links with WARGI-OPT, an optimisation model; Simulation run with user defined preferences and priorities; Often used to model drought mitigation measures; Simple, user-friendly model; Time-step is user-selected between seasons and hours

2.1.2 Optimisation-driven models

Optimisation-driven models solve a distinct optimisation model at each simulated time-step to route flows, track storages and allocate water through the network. Optimisation models choose their own operating rules (e.g. reservoir rules, allocation functions, etc...) at each time-step depending on what is optimal. This method is popular because of its relative ease of use and flexibility; optimisation-driven allocation takes some of the burden off the programmer whose code no longer has to consider every conceivable system state or outcome. However, some complex rules may be difficult to represent using optimisation and model results may not be easy to replicate in practice (Schlüter et al., 2005). Optimisation models use objective functions, decision variables and constraints. An objective function is a utility function such as the network flow programming approach of defining operating rules based on relative priorities or it can be a mathematical expression of a planning or operational objective such as an economic benefit or cost, water availability or hydropower (Wurbs, 1993). The model finds values for decision variables (e.g. water allocations or operating rules) that optimise system performance. Constraints ensure a minimum level of performance and can also be added into the objective space via a penalty function. Multiple objectives can be entered into the model as constraints for the objective function. Constraints can be factors such as reservoir discharge rates, energy consumption, minimum storage levels etc… Optimisation methods typically include linear and non-linear programming, dynamic programming and heuristic search amongst others (Labadie, 2004; Rani and Moreira, 2009). Examples of such models with user-interfaces include WATHNET (Kuczera, 1992), AQUATOOL (Andreu et al., 1996), OASIS (Randall et al., 1997), MISER (Fowler et al., 1999), MODSIM (Labadie and Baldo, 2000), RIVERWARE (Zagona et al., 2001), MIKE BASIN (Jha and Das Gupta, 2003), CALSIM (Draper et al., 2004), REALM (Perera et al., 2005) and WEAP (Yates et al., 2005). Further information on the optimisation-driven approach is given by Labadie (2004) and descriptions of modelling systems that use it can be found in Wurbs (2005a).

2.2 Performance measures

Water resource models are often used to assess the performance of different operational rules and policies or to choose between various proposed infrastructures portfolios using quantitative performance measures. By predicting how possible management options perform, models play a critical role in infrastructure expansion studies.

Performance of water resources systems can be described using an array of possible metrics. For example these metrics can be variables that quantify engineering, economic, environmental and social performance. In this thesis the reliability, resilience and vulnerability engineering performance metrics described below are stressed as they are most appropriate for the context of the case study (Thames basin) presented in this thesis. Water resource systems are complex and many more performance metrics than presented in this thesis can be used for different systems depending on context but are beyond the scope of this thesis.

Engineering performance has been traditionally described by the reliability (frequency of failure events), resilience (length of failure events) and vulnerability (magnitude of failure events) of the engineered system. Reliability is the oldest and most widely used criterion for the performance of water resource systems. Since the papers by Hashimoto et al. (1982) and Fiering (1982) resilience and vulnerability have been included as additional performance criteria. The most widely used definitions of reliability, resilience and vulnerability are those proposed by Hashimoto et al. (1982).

2.2.1.1 Reliability

Reliability can be either temporal or volumentric. Occurance reliabilty, temporal reliabilty and volemetric reliabilty are three of the most used mathematical definitions of reliability first defined by Kiritskiy and Menkel (1952) and then discussed by Klemeš (1969). The following descriptions of occurrence, temporal and volumetric reliability are described by Kundzewicz and Kindler (1995) and based on the assumption that a system can be either in a Failure (F) or Satisfactory (S) state:

1. Occurrence Reliability – the ratio of the number of time intervals in which the system never entered state S (I_s) to the total time intervals in the time horizon, represented by I_s+ I_F, with I_F representing the number of time intervals that did experience a failure:

$$Rel_O = \frac{I_S}{I_S + I_F} \tag{1.1}$$

   Time intervals are usually years or months. Reliability is more commonly written in terms of the number of failure intervals experienced:

$$Rel_{OF} = 1 - \frac{I_F}{I_S + I_F} \tag{1.2}$$

2. Temporal Reliability – the ratio of the total time (T_s) , the system spent in state S to the total time horizon, T_s+ T_F,with T_F representing the number of time spent in state F:

$$Rel_T = \frac{T_s}{T_S + T_F} \tag{1.3}$$

   Putting this in terms of the number of failure events results in:

$$Rel_{RF} = 1 - \frac{T_F}{T_S + T_F} \tag{1.4}$$

3. Volumetric Reliability – the ratio of the total quantity of water supplied to the total demand over the whole time horizon, *T*:

$$Rel_v = \frac{\int_0^T \min(Q_{SP}(t), Q_{DM}(t)dt)}{\int_0^T Q_{DM}\, dt} \tag{1.5}$$

where Q_{SP} and Q_{DM} are the total flow supplied and demanded respectively.

Hashimoto et al. (1982) define reliability by the probability that the system will be in a satisfactory state at any time, *t*:

$$Rel_H = Prob[X_t \in S] \tag{1.6}$$

where *X* represents the state at *t*. As the number of time steps approaches infinity the temporal reliability approaches Hashimoto's definition of reliability $Rel_H = Rel_T$.

The stability degree (SD) performance measure described in Hsu et al. (2008) is based on the volumetric reliability:

$$SD = \left(1 - \frac{\sum_{t=1}^{N_{ts}} WS_{ts}}{\sum_{t=1}^{N_{ts}} WD_{ts}}\right) x100 \tag{1.7}$$

where WS_{ts} is the time step flow shortage (deficit) , WD_{ts} is the time step flow demand target (required volumetric flow) and N_{ts} is the total time steps in the time horizon.

The Shortage Index (SI) first proposed by Fredrich (1975) squares the shortage term arguing that the economic and social effects of shortages are about proportional to the square of the magnitude of shortage:

$$\mathrm{SI} = \frac{100}{\mathrm{N_T}} \sum_{\mathrm{t=1}}^{\mathrm{N_{ts}}} \left(\frac{\mathrm{WS_{ts}}}{\mathrm{WD_{ts}}}\right)^2 \tag{1.8}$$

More severe shortages have a stronger influence on the SI than less severe but more frequent shortages. Unlike the previous measures of reliability higher values of SI signal worse performance.

2.2.1.2 *Resilience*

Resilience is generally defined by how quickly a system can recover from failure and return to a satisfactory state. Hashimoto et al. (1982) define this as a conditional probability that a system in state *F* will revert to state *S* in the next time step:

$$Res = Prob[X_{t+1} \in S | X_t \in F] \tag{1.9}$$

This definition is equivalent to the inverse of the mean recovery time from failure:

$$Res_H = \left[\frac{1}{\mathrm{N_F}}\sum_{\mathrm{j=1}}^{\mathrm{N_F}} d_j\right]^{-1} \tag{1.10}$$

where N_F is the total number of failure events in the time horizon and d_j is the duration of failure event *j*.

Moy et al. (1986) define the resilience as the maximum recovery time from failure. Taking the inverse of Moy's definition makes it comparable to (1.10):

$$Res_M = \left[\max_j(d_j)\right]^{-1} \tag{1.11}$$

2.2.1.3 *Vulnerability*

Vulnerability describes the expected severity of a failure when one occurs. Hashimoto et al. (1982) define vulnerability as:

$$Vul = \sum_{J \in F} s_j e_j \tag{1.12}$$

where s_j is the most severe outcome of the j^{th} sojourn in *F* and e_j is the probability that s_j is the most severe outcome of a soujourn in *F*. Hashimoto et al. (1982) and Jinno et al. (1995) used the deficit volume as their measure of vulnerability where the deficit volume is the total water deficit experienced during the entire j^{th} soujorn in *F*. In general the most severe outcome for reservoirs is s_j =0. Both studies also assumed that the probably of each failure event to be equal, thus for every failure event *j*, $e(j)=1/N_F$, the estimated vulnerability is the mean value of the deficit events *d(j)*:

$$Vul_H = \frac{1}{N_F}\sum_{j=1}^{N_F} d(j) \tag{1.13}$$

Similar to resilience, Moy et al. (1986) define vulnerability as the maximum event deficit:

$$Vul_M = \min_j\{d(j)\} \tag{1.14}$$

The Moy definitions of resilience and vulnerability are monotonic with respect to the length of the time horizon i.e. longer time horizons will have a vulnerability or resilience less than or equal to that of shorter horizons.

There has been discussion on which definition of resilience and vulnerability is more appropriate. Kundzewicz and Kindler (1995) argued that the definitions based on maximums might be better because short and insignificant failures could reduce the overall average and lead to non-monotonic measures. Kjeldsen & Rosbjerg (2004) found that the measures based on maximums did in fact show monotonic behaviour whilst those using means did not. Srinivasan et al. (1999) argued that neither definition of resilience and vulnerability alone characterised the behaviour of the system. An example similar to one presented by Srinivasan et al. (1999) is described as an illustration of how neither definition suffices for resilience.

Two sequences with 17 time steps are defined:

1. X=(S S S F F F F S S F S S F S S F S)
2. X=(S S S F F F F S S F F F F S S S S)

Under Moy's definition of resilience both cases have the same resilience. Hashimoto's definition however would reflect the fact that case 1 has a better recovery rate.
However, two different cases illustrate the shortcomings of Hashimoto's definition:

1. X=(S S S F F F S S S F F F S F F F S)
2. X=(S F S F S S S S F F F F F F F S S)

Both cases have the same resilience under Hashimoto's definition even though case 1 is better from a water manager's point of view since the duration of failures is minimal.

Kjeldsen & Rosbjerg (2004) show that there is an overlap between reliability, resilience and vulnerability This overlap is most pronounced between resilience and vulnerability which are strongly correlated. They state that it might be beneficial to abandon either vulnerability or resilience from an analysis.

2.3 Monte Carlo simulation

Monte Carlo simulation is a form of stochastic simulation. Unlike deterministic simulation where all input parameters are presumed to be known, stochastic simulation assumes that one or more input parameters are unknown (Loucks and van Beek, 2006). The unknown parameters are statistically distributed i.e. governed by known or estimated probability distributions or they can be described by an ensemble of equiprobable values. The former case describes the case of Monte Carlo simulation. Monte Carlo allows water resource system planners to evaluate how an existing system or proposed plan performs under uncertain conditions where the uncertain parameters have known and quantified probability distributions.

Monte Carlo simulation is a sampling technique and involves repeating a simulation process multiple times each time using a particular instance of the unknown variable generated from a known or assumed distribution. Repeating this process many times results in a representative sample of solutions (e.g. probability distribution of performance measures). For example let X be a random variable and the input into a complex function g (e.g. simulation model) that produces the solution Y: $Y=g(X)$. The probability distribution function (PDF) and therefore the cumulative distribution function (CDF) of X is known or estimated. A set of instances of X $(x_1, x_2 \ldots, x_i$ *etc..)*, can be created by randomly sampling its CDF. With enough samples of X a histogram of the set would approximate the PDF of *X.* Simulating the set of random input conditions results in a set of instances of solutions: $(y_1, y_2 \ldots, y_i$ *etc..)*. With enough samples of x, a histogram of the solutions would approximate the PDF of Y.

The Monte Carlo method was first developed in the 1940s during the Manhatten project (Eckhardt, 1987). Because of the secrecy of the project at the time the work was not published. Since then Monte Carlo simulation has been used in numerous studies including water resources. This stochastic method shows how system inputs described with probability distributions produce output distributions (Maass et al., 1962). For example, Prudhomme et al. (2003) used Monte Carlo simulation to generate climate scenarios to study the potential impact of climate change on the flood regime in Northern England and Scotland. Zhang and Kennedy (2006) reduced the uncertainty in the likely yield of groundwater resources in Beijing using Monte Carlo simulation.

2.4 Water resource system capacity expansion

When making water resource system plans, decision makers have to choose which options to implement, at which capacity and when to implement them in order to increase capacity as demand increases. There are often many plausible supply and demand management options to consider. When considered together, the number of possible combinations of options increases substantially. Because of limited time and computational resources, decision makers are often unable to model each combination of options (water resource system portfolio) using detailed simulation models. Optimisation methods are often used to reduce the number of alternatives (Loucks and van Beek, 2006).

2.4.1 Optimisation based capacity expansion

Capacity expansion optimisation (Loucks and van Beek, 2006; Luss, 1982; Mays, 2005; Olaoghaire and Himmelblau, 1974) is a classical planning method. Typically in capacity expansion optimisation the total costs of expansion, which comprise the objective function, are minimised. The optimisation is usually constrained where constraints include upper and lower bounds of possible options sizes, mutual dependence or exclusivity of options, system performance minima (e.g. reliability). Various optimisation algorithms can be used including mathematical programming and dynamic programming.

Linear programming (LP) is one of the most common optimization methods. In LP, the objective function and constraints must be linear and the decision variables must be continuous (Loucks and van Beek, 2006). LP is generally efficient and can be successfully used on problems with many variables and constraints. Complex water resources systems models must be linearised in order to be solved with LP algorithms (Loucks and van Beek, 2006). The limitation of continuous decision variables can be avoided by using mixed integer linear programming (MILP) where decision variables can take on integer values which represent yes/no decisions at each time step (Mays, 2005) where the binary decision is in general the decision to implement an option or not. Hsu et al. (2008) use LP to find potential bottlenecks in an existing water distribution system and propose capacity expansion alternatives to improve the efficiency of water supply. Padula et al. (2013) use

MILP to find the least-cost regional water resource system capacity expansion plan in South-East England.

Dynamic programming (DP)(Bellman, 1957) works well with multi-stage decision problems (Braga et al., 1985; Dandy et al., 1984; Martin, 1987; Olaoghaire and Himmelblau, 1974). DP decomposes a complex multi-stage problem into smaller sub-problems. Each sub-problem must be solved before the optimal solution for the original problem is found. One limitation of dynamic programing is that it quickly becomes computationally burdensome as the number of state variables increases. Braga et al. (1985) used DP to plan the proposed Juquia River reservoir system in Sao Paulo (Brazil) including reservoir capacities and scheduling.

2.4.2 Capacity expansion under uncertainty

Uncertainty in future conditions can be incorporated by implementing stochastic approaches where data is randomly sampled within a range specified by a known or assumed probability distribution. Stochastic approaches include sensitivity analysis, stochastic programming and robust optimisation.

Sensitivity analysis can be performed with Monte Carlo simulation (reviewed above). Sensitivity analysis measures the sensitivity of a solution to uncertainty in changes in the input data but it does not control or minimise it (Mulvey et al., 1995). In this way it is a 'reactive' analysis. Stochastic programming and robust optimisation on the other hand are 'constructive' approaches in that recourse variables are used to adjust model decisions once uncertain parameters are observed (Mulvey et al., 1995).

Stochastic programming (SP) (Beale, 1955; Dantzig, 1955; Wets, 1966) samples the probability distribution of the unknown parameters and finds a solution that maximises the expected outcome of a predefined function and that is feasible under all scenarios. In two-stage stochastic programming the decision variables are divided into two sets (Dantzig, 1955). In the first stage the optimisation algorithm makes decisions for certain random variables before any uncertain parameters are observed. After the realisation of random events additional information becomes known and decisions can be improved. This comes at a cost through second stage recourse variables. This second stage is used to correct any imbalance as a result of the random scenario. The objective of the optimisation is to choose first-stage variables such that the sum of first and expected value of the second stage costs is minimised. Stochastic programming has been used in capacity expansion (Ahmed et al., 2003), scheduling systems (Yen and Birge, 2006) and transportation problems (Zhao et al., 2004). Examples in water resources include SP use in water transfers (Lund and Israel, 1995) and reservoir operations (Loucks, 1968; Pereira and Pinto, 1991).

Uncertainty can also be incorporated by using robust optimisation (RO) (Mulvey et al., 1995; Soyster, 1973). Like SP, RO assumes that uncertainty is bounded within a certain range (Ben-Tal et al., 2006). However, in RO special recourse-stage variables are introduced that relax the original constraints making the solution feasible across all the unknown scenarios. A penalty term is added to the objective function each time the recourse-stage decisions are used. In this way RO develops solutions that perform well over the whole set of uncertain scenarios and are 'robust' to uncertainty. These robust solutions have objective values that do no vary widely amongst the sampled scenarios (Mulvey et al., 1995). RO has been used in a wide array of applications including telecommunication networks (Laguna, 1998) and capacity expansion in power systems (Malcolm and Zenios, 1994). Watkins and McKinney (1997) review RO in the context of water resources.

2.4.3 Economics of Balancing Supply and Demand – the current accepted planning method in England and Wales

The current planning framework that water companies in England and Wales must follow when developing their long-term supply/demand plans is called 'Economics of Balancing Supply and Demand' (EBSD) (UKWIR, 2002). Every 5 years water companies must demonstrate that their 25 to 30 year plans are able to maintain the supply-demand balance at least cost as determined by the EBSD framework. EBSD seeks socially and environmentally efficient least-cost water resource system plans that ensure a minimum level of service. EBSD is implemented using optimisation models that minimise the total economic costs of preserving the supply/demand balance given portfolios of supply and demand management (DM) options (Padula et al., 2013).

The framework considers the discounted annual capital, fixed and variable operating, social and environmental costs of the current and possible supply and demand management options. Capital costs are discounted to the end of the construction period then annuitised over each option's life. The EBSD analysis is performed on the regional scale where each subunit is represented as one Water Resource Zone (WRZ). A WRZ is a zone consisting of an interconnected subsystem whose residents experience the same likelihood of experiencing a supply deficit.

The EBSD framework is implemented with an annual time-step over a 25 to 30 year time-horizon using annual estimates of supply and demand. Each option's supply, called its 'Water Available for Use', (WAFU) is composed of its yield ('Deployable Output', DO), less any sustainability reductions (possible reduction in abstraction licenses due to future environmental regulation), losses and short-term outage allowance. DO represents the annual volume of water that can be supplied at a certain reliability ('level of service') under conditions experienced during the most severe drought in the twentieth century taking into account any water company imposed water use restrictions triggered during droughts (EA, 2011) and constrained by any environmental regulations (e.g. water quality or minimum environmental surface flows), abstraction licenses, aquifer properties and pumping, transfer and treatment capacities. The DO of a groundwater or surface water source is usually estimated with detailed water resource system simulation models and valid for an assumed level of service (frequency of supply failures). The historical records used as input data for the simulation models must go back until at least 1920 to include sufficient hydrological variability and the most severe droughts in the last century. The DO is dependent on the water company's required level of service. Assuming a higher level of service results in a lower value of DO.

Demand is the total water put into the distribution system in each WRZ and includes distribution loses though leakage. Future demand is estimated by water companies using methods such as regression analysis based on historical trends or micro-component analysis (UKWIR, 2002) and are based on different user types and future population estimate projections. Two annual demand projections are generally performed including the dry-year annual average demand which represents the annual demand during years with low-rainfall the dry year critical period demand which is defined as the average demand over a 'peak demand period', typically a week in summer.

EBSD takes into account uncertainty by incorporating a safety factor called headroom which represents an annual aggregation of all sources of supply-demand uncertainty at the WRZ-level. Headroom is the minimal acceptable buffer between supply and demand to guarantee supply reliability (levels of service) by water companies. Uncertainty components include, but are not limited to, possible reductions in abstraction licenses and imports, inaccuracy of estimated output of new sources, and uncertainty in yield because of climate change.

2.4.3.1 Least-cost solution to the planning problem

Some WRZs in the system may exhibit a supply and demand imbalance over the planning time horizon. Planners identify a range of feasible supply and demand management options that could re-establish this supply-demand balance. Each possible option has an estimated DO and cost which is broken down into financial, environmental and social components. Financial costs include capital and variable and fixed operating costs.

An optimisation algorithm is then employed (often a mixed-Integer linear program) to find the least financial, social and environmental cost schedule of options that satisfies the supply/demand balance (including headroom) over the time horizon at the required levels of service. A visualisation of the EBSD framework can be seen in Figure 2.1

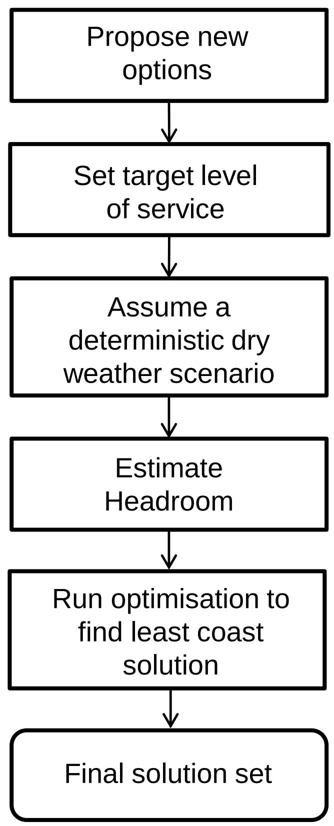


Figure 2.1 Flow chart of the Economics of Balancing Supply and Demand water resource system planning framework.

2.4.3.2 Benefits and limitations of the EBSD least-cost optimisation approach

By using annual aggregate estimates of supply, demand and uncertainty (headroom) the EBSD framework simplifies the water supply planning problem to its core: ensuring the supply demand balance is maintained with a safety buffer at minimum economic cost. Formulating the problem in this way allows it to be solved with an optimisation model using commercial mixed integer programming optimisation solvers.

However, this simplification requires making certain limiting assumptions on how the problem is formulated. EBSD models are single objective (minimisation of total aggregated economic costs) while the performance of real water supply systems is inherently judged by multiple criteria (e.g. service reliability, environmental performance, and energy use in addition to costs). In EBSD these criteria must be commensurated into economic costs. EBSD assumes that supply (DO) estimates are generally static. In reality over the simulation time-horizon, yields may change or fluctuate with climate, natural hydrological variability and land-cover/land-use practices. Furthermore, EBSD assumes that each year's storage supplies are unrelated to the previous year's storage levels. This assumption is not appropriate for areas where over-year storage is significant. In such cases more complex formulations are required to track storage levels and other water management variables (Loucks et al., 1981).

The EBSD capacity expansion planning method does have benefits. Regulators in England and Wales demand that water companies maintain their supply-demand balance at least economic cost making the EBSD method institutionally appropriate in this context. Optimisation models encounter many challenges in real-world water resource planning (Rogers and Fiering, 1986) and the fact that EBSD is used by different actors on the national level is a significant benefit. The EBSD framework is able to consider a large number of possible supply and demand options. In addition to the least-cost portfolio, the frameworks results provide the least-cost annual schedule of implementation of the selected options.

2.5 Water resource planning methods investigated in this thesis

One limitation of current capacity expansion methods described in the research problem is that they generally use simplified and aggregated system models that have difficulties representing non-linearities. Water resource system simulators do not have these limitations. Simulators are able to model water resource systems in detail and are able to represent non-linear operating rules. They are also able to calculate system performance in multiple performance criteria (i.e. reliability, resilience, vulnerability, supply shortage etc…). Employing a simulation model in the planning process rather than an aggregated optimisation model may prove beneficial.

Another limitation of current methods is that they grapple with the inherent uncertainty of future conditions. For example the Economics of Balancing Supply and Demand method (EBSD) strives for an optimal solution for the expected future (given an uncertainty buffer, headroom). Optimal solutions may not meet performance requirements if the future that comes to be deviates from the expected future.

The methods chosen to be investigated in this thesis may alleviate these limitations. These methods include Robust Decision Making (RDM), Info-Gap Decision Theory (Info-Gap), and an approach that combines multi-objective evolutionary optimisation with simulation (MOEA). All three of these methods use a detailed simulating model that is able to represent non-linearities and is able to produce multi-criteria performance metrics. RDM and Info-Gap are two methods that seek robust, rather than optimal solutions. Solutions are robust when they perform satisfactorily well in a wide range of futures rather than optimally in a few. The MOEA implementation does not seek robustness, but it allows decision makers to visualise the trade-offs between potential planning strategies making the method suitable for bottom-up planning.

2.5.1 Knightian uncertainty and robustness

Planning models grapple with the inherent uncertainty of future conditions when the statistical distributions of future conditions are unknown or not trusted. Under such 'Knightian' uncertainty (Knight, 1921) uncertainty is unquantifiable and the most likely realisation of the future is unknown. Instead of using the term 'Knigntian' uncertainty Lempert et al. (2003) use 'deep' uncertainty which they define as uncertainty where "analysts do not know, or the parties to a decision cannot agree on, (1) the appropriate conceptual models that describe the relationships among the key driving forces that will shape the long-term future, (2) the probability distributions used to represent uncertainty about key variables and parameters in the mathematical representations of these conceptual models, and/or (3) how to value the desirability of alternative outcomes."

In such situations of 'deep' or 'severe' uncertainty, methods that rely on traditional Bayesian decision analysis to characterise uncertainty using probability theory may not be appropriate (Groves and Lempert, 2007). Recent research has argued that in these conditions, it is more appropriate to strive for robustness (Ben-Haim, 2001; Dessai and Hulme, 2007; Lempert et al., 2006a; Lempert and Collins, 2007) rather than optimality. A 'robust' system performs satisfactorily, or satisfices (Simon, 1959) performance criteria, over a wide range of uncertain futures rather than performing optimally over the historical period or a few scenarios.

2.5.2 Robust Decision Making

Robust Decision Making (RDM) is a planning framework designed to help decision makers formulate robust plans for the future under conditions of Knightian, or 'deep' uncertainty (Lempert and Collins, 2007). RDM represents such uncertainty by considering system performance under a wide range of futures scenarios. RDM favours the concept of robustness over optimality and assumes that a strategy that is able to satisfice (Simon, 1959) minimum performance criteria over a wide range of plausible futures is preferable to one that performs optimally in a few.

RDM helps decision makers develop new strategies that are more robust than those initially considered (Hall et al., 2011a). In RDM, the initial preferred plan is evaluated under a wide spectrum of plausible futures. RDM characterises the vulnerabilities of the initial strategy using a process known as s*cenario discovery* (Bryant and Lempert, 2010; Groves and Lempert, 2007; Lempert et al., 2006a) which rigorously identifies sets of future conditions, or 'scenarios', where the system under the preferred plan would be under most stress. Decision makers use this information to improve the candidate strategy generating new strategies that hedge against those conditions which most frequently cause system failures. The new strategies can be resubmitted into the RDM framework and the process repeated iteratively until a suitably robust strategy is found.

RDM analysis begins with the selection of one or more candidate strategies. Sometimes current policy can be selected as the candidate strategy or it can be one or more proposed future plans. Other times it can be chosen through a traditional utility or regret analysis (Lempert and Groves, 2010). The second step characterises the vulnerabilities of the candidate strategy by identifying under which combination of uncertain conditions it fails to meet performance criteria. To identify the vulnerabilities a trusted simulation model calculates system performance criteria for different combinations of input conditions representing a wide spectrum of plausible future states. Each run is evaluated as a success if it is able to satisfice minimum performance criteria or a failure if it is not. Performance criteria are either absolute thresholds where a strategy fails if its performance crosses a certain threshold such as a cost limit, or they are relative, where the performance of the candidate strategy is compared to the performance of an ideal strategy in the same state of the world, for example using regret (deviation from optimality) (Savage, 1954). Analysts then use cluster-finding algorithms to identify under which combinations of future conditions a particular strategy becomes vulnerable. Failure clusters are regions of the solution space bounded by one or more dimensions that have a relative high density of failure points compared to the density in the whole of the solution space.

In the final step planners propose improvements to address the vulnerabilities uncovered in the previous step developing alternative strategies or discarding the strategy altogether if its vulnerabilities are unacceptable. The process returns to the second step to analyse an improved strategy or to the first step for a new strategy, and the process is repeated until planners agree on a 'robust' strategy. After this process, planners produce trade-off summaries which are used to compare alternative strategies.

Groves and Lempert (2007) used RDM to identify vulnerabilities of the California Department of Water Resources' California Water Plan. Lempert and Groves (2010) apply RDM to identify climate change vulnerabilities of the Inland Empire Utilities Agency's 2005 Integrated Water Resource Plan and to develop a more robust plan including adaptive strategies.

2.5.3 Info-gap Decision Theory

First developed in the 1980s by Ben-Haim (2001) Info-gap is a non-probabilistic method used for evaluating the robustness of decisions under conditions of 'severe' uncertainty. Severe uncertainty is defined by Ben-Haim as conditions upon which to base a decision are scarce. Severe uncertainty is the term used by Ben-Haim to describe Knightian or deep uncertainty. Conditions of severe uncertainty lead to an 'information gap' between what is known and what needs to be known in order to make a sound decision.

Info-gap analysis requires a model of the physical system that predicts the outcome of possible decisions (e.g. simulation model) based on an Info-gap uncertainty model and minimum performance requirements. The Info-gap approach then uses a 'robustness' and 'opportuness' analysis to compare possible decisions (described below).

Info-gap represents uncertainty as a group of nested sets defined on the space of the decision-relevant variable(s) *u*. The best estimate of *u* is defined as $\tilde{u}$ and is assumed to be a poor guess of the true value(s). Uncertainty is modelled as a set of expanding nested sets originating from the best estimate now referred to as the central-estimate. Info-gap parameterises the deviation from the central estimate $\tilde{u}$ by *h*, which it calls a horizon of uncertainty such that $h\colon h\ \geq 0$. The group of nested sets defined in Info-gap is thus written as the uncertainty model: $U\ (h, \tilde{u})$. Figure 2.1 shows a visualisation of an Info-Gap uncertainty model.

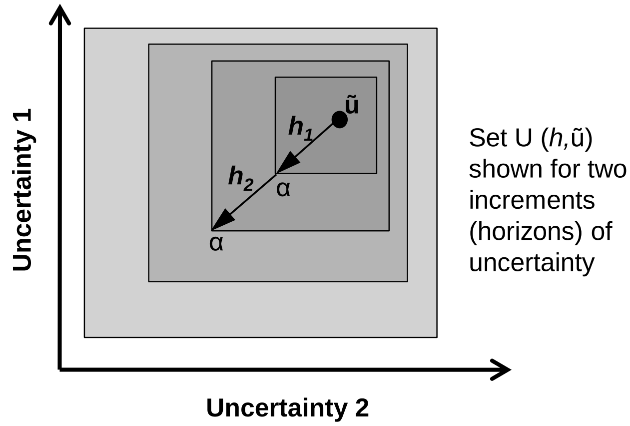


Figure 2.2 Schematic of an Info-Gap uncertainty model showing the scaling (h) of each interval (horizon) of uncertainty (a) from a best estimate ($\tilde{u}$). Note that the uncertainty model can be asymmetric to better represent the uncertainty surrounding the best estimate.

When the uncertain parameters are independent from one another the Info-gap model assumes a cuboid shape. Assuming covariance between parameters results in elliptical models. The uncertainty model can also include constraints on parameters or the interval between $\tilde{u}$ and *u* can be reduced in one or more dimensions if the maximum value of a parameter is close to the central estimate.

The last step of the Info-gap method is to compare alternative strategies (decisions), q_i, by evaluating a reward function $R(q_i,u)$ at different horizons of uncertainty, *h*, in $U\ (h, \tilde{u})$. In the water resources context the reward is generally referred to as performance, *Π*, and is calculated using simulation models. At each horizon of uncertainty there is a range of performance specified by the minimum and maximum levels of $\Pi\ (q_i,u)$ where the minimum level is defined as *robustness* and the maximum as the *opportuneness*.

Info-gap employs the idea of *robust-satisficing* (Ben-Haim, 2005) where strategies that are able to perform acceptably well, or satisfice (Simon, 1959) minimum performance criteria over a wide range of conditions are favoured. Following this concept, the analyst sets a minimum level of performance, Π_c. The robustness function defines the maximum level of uncertainty that can be tolerated whilst respecting Π_c:,

$$\hat{h}(q_i, p_c) = max\left\{h\colon \min_{u \epsilon U(h,\tilde{u})} \Pi(q_i, u) \geq\ p_c\right\} \tag{2.1}$$

In general robustness decreases as the minimum performance increases and as uncertainty increases, system performance decreases: $\Pi(q_i u,) \leq \Pi(q_i, \tilde{u})$. Robustness considers the case where uncertainty results in conditions that are worse than the best-estimate.

Uncertainty can also lead to more favourable conditions resulting in performance windfall and this is taken into account in the opportuneness function which defines the minimum level of uncertainty necessary to reach a 'windfall' level of performance, p_w:

$$\hat{\beta}(q_i, p_w) = min\left\{h\colon \max_{u \epsilon U(h,\tilde{u})} \Pi(q_i, u) \geq p_w\right\} \tag{2.2}$$

The Info-gap analysis often produces summary visualisations that present robustness and opportuneness as a function of p_c and p_w with the horizon of uncertainty on the y-axis and performance on the x-axis. Robustness and opportuneness curves are then calculated for each strategy using the same uncertainty model allowing the direct comparison of each strategy. The robustness curves show the maximum level of uncertainty that can be tolerated whilst still respecting the minimal performance criteria whilst the opportuneness shows the minimal level of uncertainty that is needed to obtain a certain level of windfall (Hall et al., 2011a). Often robustness and opportuneness curves of different strategies cross showing that for example one strategy can be more robust than another up to a certain minimum performance but less robust than at a lower minimum performance. The choice of strategy therefore depends on the level of performance considered satisfactory. Using information obtained from the robustness and opportuneness curves and taking into consideration the possible crossing of curves the Info-gap method can help analysts identify robust strategies.

Info-gap has been used in a variety of different contexts including flood risk management (Hine and Hall, 2010) and risk management of invasive species (Yemshanov et al., 2010). Hipel and Ben-Haim (1999) apply Info-gap to represent different sources of hydrological uncertainty. McCarthy and Lindenmayer (2007) employ Info-gap on a water resources - timber production management problem in Australia to determine the robustness of planting strategies to uncertainties in wildfire return periods and knock-on effects on municipal water supply.

2.5.4 Multi-objective evolutionary optimisation combined with simulation

Optimisation algorithms such as mathematical programming and dynamic programming have for decades been used to solve water resource system capacity expansion problems (Loucks et al., 1981; Loucks and van Beek, 2005; Mays, 2005; Revelle, 1999). Such optimisation methods have known success but also have limitations including the difficulty of representing water system non-linearities, the diversity of discrete options and their potential to mask important performance trade-offs for real systems when the optimisation is performed over few objectives (Woodruff et al., 2013). Water systems often use non-linear rules and are frequently subject to nonlinear cost and benefit functions. Their complexity may mean that aggregation and simplification of performance measures are often required when using classical optimisation methods. Often minimising costs has been the sole objective with non-commensurable objects translated into costs. When classical optimisation methods address multiple objectives, the relative weightings of each of the objectives must be pre-assigned, or changed iteratively. In real systems planners seek to simultaneously minimise expenditures whilst maximising performance criteria such as reliability and ecological benefits. Given that the historical consensus view that the water planning problem is inherently multi-objective (Cohon and Marks, 1975; Haimes and Hall, 1977) it is critical to move beyond classical commensuration approaches that require a single common unit of measure (typically monetary). The interaction of multiple criteria in the context of investment opportunities has been long discussed in various fields (Brill et al., 1982; Major, 1969) and water is no exception (Maass et al., 1962). Water resource system simulators are able to incorporate non-linearities and explicitly calculate system performance using multiple criteria without the need to translate non-commensurable metrics into a single monetary metric. In combined multi-objective evolutionary optimisation and simulation, a water resource simulator acts as the objective function whose solution is the performance output of the model.

The addition of multiple performance objectives in the planning problem can reduce the possibility of human decision biases (Brill et al., 1982) such as ‘cognitive myopia’ or ‘short-sightedness’ (Hogarth, 1981) which can negatively bias planning decisions. This typically occurs in low-dimensional problems when managers feel they have sufficient knowledge about their system’s behaviour but may in fact lack a full understanding of innovative possibilities (Woodruff et al., 2013). A second decision bias was described by Gettys and Fisher (1979) as “cognitive hysteresis”, where decision makers’ pre-conceptions limit their incorporation of new ideas in their formulations of the future. These biases can lead to under- or over-estimation of reliability risks as shown by Kasprzyk et al. (2009) where adding additional objectives and decision variables led to alternative solutions that met reliability requirements at lower cost. Kollat et al. (2011) demonstrate how adding objectives can change the objective space and decision makers’ preferences about the system's performance. They show that considering only two objectives can result in "extreme" solutions located at the edges of the objective space where they fail to satisfy other decision relevant concerns. Fogel (1997) argues that heuristic global optimisation techniques such as evolutionary algorithms (EAs) can help to overcome our biases by discovering new solutions to new problems.

Evolutionary algorithms imitate the process of natural evolution and have strongly contributed to the water resources literature as reviewed by Nicklow et al. (2010). Evolutionary algorithms are heuristic search algorithms that mimic the biological process of natural selection to produce an approximation of the Pareto optimal solution space. The search is an iterative process that begins with an initial population of solutions whose performance is then evaluated. Better performing solutions survive into the next generation. The algorithm uses the evolutionary principles of crossover, selection and mutation to introduce variation into the surviving population before producing the next generation of solutions. Evolutionary algorithms use randomness to their advantage opening many pathways to find solutions (Hofstadter, 1995). A detailed review of evolutionary algorithms can be found in Coello Coello (2005). Evolutionary optimisation has been applied to reservoir rule design (Chang and Chang, 2009; Chen et al., 2007; Kim et al., 2008; Kim et al., 2006; Mortazavi et al., 2012a; Reddy and Kumar, 2006), the optimisation of well placement and operation (Park and Aral, 2004), groundwater monitoring and management (Cieniawski et al., 1995; Emch and Yeh, 1998; Erickson et al., 2002; Farmani et al., 2009; Kollat and Reed, 2006; Mantoglou and Kourakos, 2007), water distribution (Farmani et al., 2006; Kapelan et al., 2005), flood risk management (Woodward et al., 2013),urban water supply operation (Cui and Kuczera, 2003; Cui and Kuczera, 2005; Mortazavi et al., 2012b) and water resource system portfolio and infrastructure selection (Arena et al., 2010; Kasprzyk et al., 2009; Mortazavi et al., 2012a; Yang et al., 2007). Evolutionary algorithms have been shown particularly suitable for multi-objective water management applications (Nicklow et al., 2010; Reed, 2012) when linked to non-linear simulation models. Simulators are often developed over decades by water management agencies that include customized performance metrics which become trusted measures to evaluate management alternatives. Many objective evolutionary search is appropriate for water system planning where there are many goals for the system's performance. In such an approach, simulation models evaluate the optimisation model's objective function, which means the full flexibility and descriptive ability of simulation models is harnessed (Labadie, 2004).

Multi-objective evolutionary algorithms seek an approximation to the set of Pareto optimal solutions, where an improvement in one objective will simultaneously degrade the performance in other objectives (Coello Coello, 2005). Figure 2.2 illustrates this concept: although solution A performs better in objective f_2, solution B performs better in objective f_1. There is a trade-off between objectives f_1 and f_2; decision makers must assess how much they are willing to sacrifice the performance of one objective in order to improve the performance of the other. The set of all Pareto points is referred to as the Pareto optimal set and when plotted constitute the Pareto frontier.

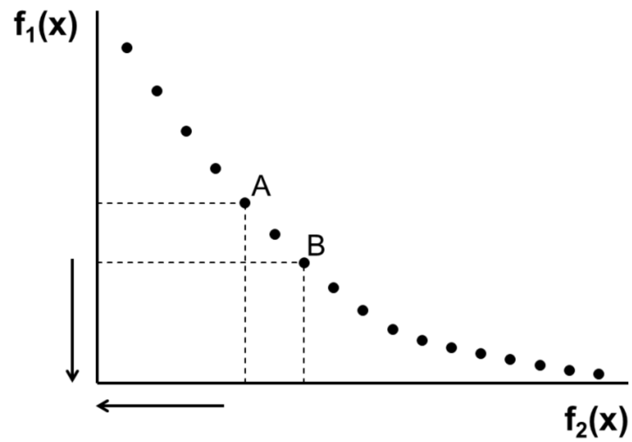


Figure 2.2 Pareto optimal front of a two objective problem showing a trade-off between objectives f_1 and f_2. Arrows indicate the direction of best performance.

Rapid and highly interactive visualisation of 'Pareto-optimal' solutions including their corresponding design components is critical for understanding complex trade-offs for applications with large numbers of objectives. Many-objective visual analytics ('visual analytics' for short, (Woodruff et al., 2013) refers to emerging software packages that facilitate this process. The approximations of Pareto optimal sets usually contain a large number of solutions that increases rapidly with the number of objectives considered. It is important not only to visualise these solutions in multi-dimensional space but also to be able to isolate promising solutions with adequate justification. As the number of trade-off dimensions increases the role of visual analytics becomes more central to the design and decision making process. Many water related problems are complex and formulating such problems appropriately usually requires a continuous learning process and the exploration of multiple problem formulations (Kasprzyk et al., 2012; Zeleny, 2005).

3 IRAS-2010

3.1 Introduction

Water resource simulation models help water managers plan, design and operate water systems (Loucks et al., 1981; Loucks and van Beek, 2005). Simulation models employ user-defined operating and allocation rules to predict flow and storage of water throughout the system over time. They help predict how different management rules and infrastructure configurations react to adverse conditions such as droughts, flooding or long-term change.

This chapter describes the generalised IRAS-2010 water resource management simulation model and its application to the Thames basin water system in South East England. The first parts of this chapter describe IRAS-2010's history, functionality, equations and simulation procedure. Next an IRAS-2010 model of the Thames water resource system is described. Results of the IRAS-2010 Thames model are compared to those of a calibrated planning model of similar resolution maintained by the Environment Agency of England and Wales. Finally, limitations and advantages of IRAS-2010 and future development are discussed.

3.1.1 IRAS-2010 History

The original IRAS (Interactive River-Aquifer Simulation) program (Loucks et al., 1995) was developed at Cornell University and the International Institute for Applied Systems Analysis and released in 1995. IRAS was used in several published and unpublished studies around the world as a tool for addressing regional, national and international water basin management (Loucks and Bain, 2002; Loucks et al., 1995; Salewicz and Nakayama, 2004). Using IRAS Brandgo and Rodrigues (2000) conducted a study of the downstream effects in Portugal of reservoir storage capacity increases on Spain's Guadiana river.

IRAS-2010 is a new code based on the 1995 version. Improvements include (1) an improved calculation algorithm for water deficits, (2) the ability to associate demand link diversions to any demand node, (3) more flexible reservoir group balance rules, (4) demand restrictions during water supply shortfalls, (5) long-term water demand changes, (6) energy costs and hydropower revenues, (7) more detailed aquifer interactions, (8) calculation of channel dimensions and flow velocity, (9) performance measure output, (10) support for batch runs (e.g. for stochastic climate change studies), (11) addition of text-based input and output files and leap year support. More information on these changes is found in Section 3.4 and Table 3.2. IRAS-2010's Fortran source code was optmised for speed by reducing file manipulation, caching data, and transforming input data into a structured binary format. Using data structures gives users the possibility to modify network parameters without having to re-read input files, increasing the efficiency of multiple run simulations for stochastic simulations. The resulting modelling system produces fast models; for example the London water resource system model described below runs in 1 second on a 2 GHz computer when using a weekly time-step over an 85-year time horizon.

3.1.2 IRAS-2010 Functionality

IRAS-2010 is a rule-based water resource management simulator that models water flows and storages, single and joint reservoir releases, time-varying water consumption, hydropower production and pumping energy use**.** Salient IRAS-2010 features include computational speed, the ability to realistically represent a wide range of water management actions and conditions, and a customizable user-interface and online open-source code management (www.hydroplatform.org).

An IRAS-2010 model represents the system as a network composed of nodes and links of various types. Nodes can be diversions, natural lakes, reservoirs, aquifers, wetlands, gauge sites with a defined time-series flow, demand and consumption sites. Demand nodes have either flow or storage demand targets. When demand nodes experience a deficit they call for water from links or supplemental reservoir releases.

Links represent unidirectional or bidirectional natural or engineered flow paths between two surface and/or groundwater nodes. IRAS-2010 has three types of unidirectional links: 'diversion', 'demand' or 'natural' links. Diversion links represent canals or pipelines and require diversion functions to indicate how much water is abstracted (Figure 3.5). A demand link transmits water to a demand node whose allocation comes from either surface storage (reservoirs) or river reaches. Simple hydrologic river flow routing routines and loss functions can be activated on unidirectional links. Bidirectional links model flow to or from aquifers (along 'groundwater' links) or flow to and from wetlands (along 'surface' links). Storage nodes representing reservoirs, lakes, aquifers or wetlands use rating tables to define surface area, elevation, seepage and release as a function of storage volume. Lakes release water according to rating tables and reservoirs use rating tables to define minimum and maximum release rates within user-defined storage zones. Evaporation and rainfall rates can be associated with surface storage nodes. Wetlands and aquifers use volume-head tables defined on their bidirectional links to determine the direction of flow. Additionally, simplified aquifer-aquifer and aquifer-surface water interactions can be represented.

IRAS-2010 estimates hydropower and pumping energy production or requirements on relevant nodes. Demand modelling features include annual demand growth, storage-level triggered water demand reductions and flexible scalar, seasonal or time-series specification of water demands. This allows simulating realistic water use restrictions and customized water demand change patterns. All IRAS-2010 parameters can vary seasonally and annually. Designated 'gauge' sites (locations having a time series of natural unregulated flows) can use flow factors to modify the flow (e.g. for scenario analysis or climate change impact modelling).

IRAS-2010 generates a results file with time-series of all modelled state variables at each network location and time step. A performance summary file currently outputs a variety of scalar indicators for different nodes types and could be adapted to include further performance metrics. Reliability, resilience and vulnerability performance indicators adapted from Hashimoto et al. (1982) are calculated at storage nodes. These indicators show how many times user-defined storage thresholds were violated and their average and maximum duration. Another reliability indicator gives an average annual reliability probability for each threshold. Energy use or production resulting from pumping or hydropower is summarised and includes energy costs or revenue calculated from user-defined energy prices. Generic energy and costs can be included at any network location by specifying energy requirements per unit of water. Finally two water supply indices, Shortage Index (SI) and Stability Degree (SD) (Hsu et al., 2008) are quantified at each water demand.

3.2 IRAS-2010 computer program

IRAS-2010 is programmed in Fortran using procedural programming, meaning it organizes tasks into subroutines. All model functionality is included in subroutines; custom scripting of specific network elements is not possible. It is an open-source code distributed under a general public license with an online code management website (wiki, code repository, bug reports, etc. accessed from www.hydroplatform.org). IRAS-2010 does not have its own user-interface; instead it is available as an add-in or 'app' within HydroPlatform, an open-source generic user-interface and data manager for water models (Harou et al., 2010). IRAS-2010 can also run independently with the user generating input files manually following available guidelines (http://sourceforge.net/projects/iras/). Because both IRAS-2010's code and separate user-interface are open-source, they can be customized for particular applications.

IRAS-2010 runs on a yearly loop. The year is divided into time steps, each having a user-specified number of days. For example, a week long time step uses 7 days, and a monthly time step uses 30 days. IRAS-2010's internal algorithms break each time step into subtime steps. The simulation procedure loops summarised in Figure 3.2 are run for each subtime step. The user-defined number of sub time steps defaults to 10. The more subtime steps there are, the more precise calculations become especially when reservoir rules, aquifers and wetlands or demand and source nodes are part of the network and looped flows exist (Loucks et al., 1995). However, including more subtime steps results in increased run times. The user must therefore consider the trade-off between increased precision with more subtime steps and the corresponding longer run times.

IRAS-2010 supports inputs in any units. The user must provide conversion factors that convert user input units into internal IRAS-2010 units (Table 2).

Table 3.1 IRAS-2010 internal units.

Parameter	Nodes	Links
Length	m	M
Area	m^2	m^2
Volume	Million m^3 (Mm^3)	Million m^3 (Mm^3)
Flow and Seepage	Mm^3/day	Mm^3/day
Evaporation / Rainfall/ Link Loss	m/day	m/day
Power	kW	-
Hydraulic Conductivity (K)	-	m/day

3.3 IRAS-2010 Equations

3.3.1 Hydrologic Routing in Unidirectional Surface Links

When the time-step of simulation is shorter than the time it takes for flow to travel through a river or canal reach, it may be necessary to use hydrologic routing techniques to account for water conveyance travel time. IRAS-2010 can perform hydrologic flow routing using two methods. The first method relates the outflow at link *l*, $Qout_l$ in user flow units to the total water volume in the link, V_l ,using the following equation:

$$Qout_l = aV_l^{\ b} \tag{3.1}$$

Where *a* and *b* are user calibrated routing parameters specific to the link and user flow units. The outflow, $Qout_l$, depends on the detention storage in the link.

The second method is the cascading reservoirs method; it splits the link into a user-defined number of cascading sub-links (*sl*) whose outflows, $Qout_{sl}$, are related to their inflows, Qin_{sl}, according to:

$$Qout_{sl} = (a * Qin_{sl} + b * V_{sl})^c \tag{3.2}$$

Where V_{sl} is the sub-link volume and *a*, *b*, and *c* are user calibrated routing parameters. The input of the next reservoir in the sequence is the output of the previous one.

3.3.2 Link Cross Section Geometry

If routing is enabled, flow depth [m], width [m] and velocity [m/subtime step] can be calculated. Width can then be used for link loss calculations.

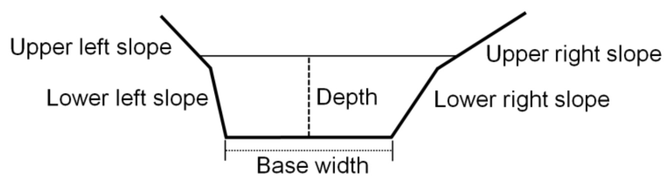


Figure 3.1 Reach cross section geometry considered in IRAS-2010 showing slopes of various angles.

Before these link calculations begin, the link's surface area and width at the link's lower banks is calculated (Figure 3.1). Calculation of flow width, depth and velocity begins by averaging the volume of the link at the beginning of the subtime step and the volume at the end of the subtime step, $\overline{\mathrm{V}}_{\mathrm{l}}$,to account for routing and losses. Using the link's average volume and the flow rate through the link, Q_l [now in m^3 /subtime step] the residence time of the link, T_l [subtime steps] is

$$T_l = \frac{\overline{\mathrm{V}}_{\mathrm{l}}}{Q_l} \tag{3.3}$$

The velocity of the flow in link is then its length, l_l [m] divided by its residence time:

$$Velocity_l = \frac{l_l}{T_l} \tag{3.4}$$

The area, A_l [m^2], of the link is calculated using the link volume:

$$A_l = \frac{\overline{\mathrm{V}}_{\mathrm{l}}}{l_l} \tag{3.5}$$

3.3.3 Unidirectional Surface Link Losses

Losses in unidirectional surface links can be calculated by three methods. The simplest method uses a loss rate vs. flow rating table whilst the other two methods determine link loss by using a loss rate, lr_l [m/day], and the link's surface area: $Qloss_l = lr_l * W_l * l_l$ (3.6) where W_l [m] is the average width of the flow channel at the water level and l_l [m] the length of the link. The second method interpolates W_l from a user defined W_l vs. flow rating table whilst the third obtains W_l from link cross section calculations which are described in Section 3.3.2.

3.3.4 Bidirectional Groundwater Links

Bidirectional groundwater links can employ user-defined flow tables to define the direction and magnitude of flow based on piezometric head on either side of the link. Additional methods exist for calculating the flow through groundwater (*gw*) bidirectional links based on Darcy's law:

$$Qgw_l = K_l * A_l * \frac{(y_1 - y_2)}{l_l} \tag{3.7}$$

where Qgw_l refers to the flow in the groundwater link l, K_l is the hydraulic conductivity [m/day], A_l is the area through which the flow occurs [m^2], y_1 and y_2 [m] are groundwater level elevations read from rating tables, and l_l [m] is the length over which the flow occurs. Subscripts 1 and 2 denote the nodes at either side of the groundwater link. A positive Qgw_l denotes flow to node 2 whilst a negative flow is a flow to node 1. Groundwater flow can be estimated between aquifers, between a storage node and an aquifer or between a surface water link and an aquifer.

3.3.5 Hydropower and Pumping

Hydropower power generation and pumping energy usage calculation begins by determining the head difference, ΔH [m] between the nodes: $\Delta H = y_1 - y_2$ where y_1 and y_2 [m] are input and output node elevations respectively. Elevation at storage nodes is calculated dynamically from storage-elevation rating tables. If flow through bidirectional links is directed towards the output node, hydropower is produced, if it is flowing towards the input node then pumping energy is consumed.

For hydropower, the head is redefined if the turbine elevation is higher than that of the downstream node $\Delta H_{hp} = \min[\Delta H, y_1 - y_{turbine}]$ (3.8). The power produced, P [W], is calculated using the general hydropower equation including plant efficiency

$$P = g * \rho * Q_l * \Delta H_{hp} * efficiency \tag{3.9}$$

where g [m^2/s] is the gravity constant, ρ the density of water and Q_l [m^3/s] the flow through the link.

The energy produced, E[Wh] is power multiplied by the number of hours in a subtime step:

$$E = g * \rho * Q_l * \Delta H * efficiency * hours\ per\ subtime\ step \tag{3.10}$$

For this calculation the flow through the link, Q_l, should be in m^3/s. Because the program's internal flow units are in Mm^3/subtime step, Q_l is converted leading to:

$$E = 2725 * \rho * Q_l \left(\frac{Mm^3}{\text{subtime step}}\right) \Delta H * efficiency \tag{3.11}$$

This is the energy that the plant should theoretically produce per subtime step. The actual energy produced is subject to its capacity at its rated head, $hCap$ [Wh], and the plant factor (*pf*) which is the fraction of the time the plant is enabled:

$$E_{max} = hCap * pf * hours\ per\ subtime\ step \tag{3.12}$$

If $E > E_{max}$ then E_{max}becomes the energy produced in the subtime step by the plant. If pumping is performed on the link energy is consumed and Equation (3.11) is instead divided by the efficiency.

3.4 IRAS-2010 Simulation Algorithm

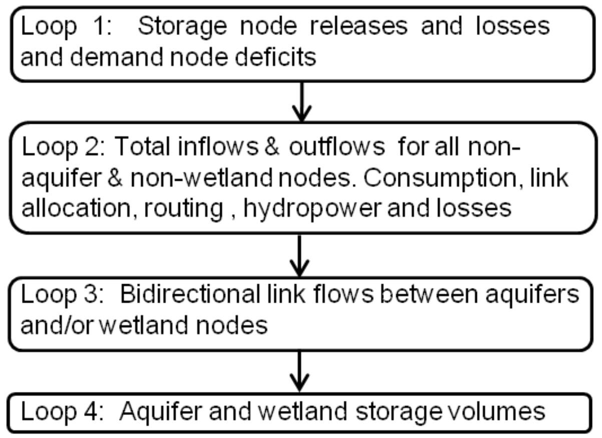


Figure 3.2 The IRAS-2010 simulation algorithm is divided into four loops that are run at each subtime step. Adapted from Loucks et al. (1995).

At each subtime step IRAS-2010 executes a series of instructions organized into four loops to calculate storages, flows, allocations and consumptions (Figure 3.2). The first loop calculates the demand targets and deficits at demand nodes and determines reservoir releases required to satisfy these deficits. Lake outflows and seepage losses are also calculated in this loop. The second loop calculates inflows and outflows of all non-aquifer and non-wetland nodes by propagating surface storage releases and natural flows from gauge nodes downstream along all unidirectional links. Flow through bidirectional links connected to non-aquifer and non-wetland nodes are also determined in this loop. The third loop calculates the remaining bidirectional link flows and the fourth loop updates wetland and aquifer storages.

3.4.1 Loop I – Releases and losses from surface storage

The first loop calculates demand deficits of demand nodes and releases and losses from surface storage nodes.

Lake releases are calculated according to storage-volume rating tables. Reservoir releases can be demand-driven target releases or supply-driven using reservoir rules and balancing functions. IRAS-2010 makes several passes through the network calculating each release type independently before final outflow calculations are performed.

The first pass determines demand-driven release targets for reservoirs. IRAS-2010 first determines the demand deficit for each demand node. Demand deficits can either be in volume units or flow units depending on if the demand node is a storage or flow node. For storage demand nodes IRAS-2010 computes subtime step (*st*) deficit [Mm^3] as follows

$$Deficit_{dn}^{st} = vTarget_{dn}^{st} - V_{dn}^{st} \tag{3.13}$$

Where *dn* is the demand node index, st is the subtime step index, $vTarget$ [Mm^3] is the target storage for the demand node and V_{dn}^{st}[Mm^3] is the real-time subtime step storage.

Targets for flow demand nodes [Mm^3/st] must consider 'passive' water that enters a node without upstream managed releases or abstractions. Passive water is taken into account by extrapolating how much water would reach demand nodes over a time step. No managed water allocations or releases are made to demand nodes using this method at the first subtime step. This allows the algorithm to estimate how much natural flow would have reached the demand node at the end of the time step without managed allocations and releases. If the algorithm determines that the demand node will experience a deficit it estimates how much water should be released from reservoir nodes and/or allocated to the node in the next subtime step by calculating the next subtime step's deficit with Equations (3.14) and (3.15). This extrapolation procedure is repeated until the end of the time step taking into account managed releases from previous subtime steps to determine how water should be allocated in each subtime step.

At each subtime step (except the first) the extrapolation estimates demand deficit by predicting the total end of time-step (*t*) inflow, $Qexpected_{dn}^{st}$[Mm^3]:

$$Qexpected_{dn}^{st} = \sum_{1}^{st} Qin_{dn}^{st} - \sum_{1}^{st} Deficit_{dn}^{st} * \frac{(tst - st + 1)}{(st - 1)} \tag{3.14}$$

Where the first term is the total inflow into the node up to the current subtime step and the second term is the sum of all the subtime step deficits (calculated below) from earlier subtime steps and tst is the total number of subtime steps in the time step.

The subtime step deficit [Mm^3/st] is the total time step target demand, $qTarget_{dn}^{t}$, [Mm^3/t]: less any demand reductions, the total real-time inflow and the expected inflow divided by the total subtime steps left in the time step,

$$Deficit_{dn}^{st} = \frac{qTarget_{dn}^{t} - qTarget_{dn}^{t} * f_{Red} - \sum_{1}^{st} Qin_{dn}^{st} - Qexpected_{dn}^{st}}{(tst - st + 1)} \tag{3.15}$$

Where f_{Red} is a demand reduction factor.

If passive water does not enter a demand node, $Deficit_{dn}^{st}$ can be calculated without the extrapolation procedure described above. The method calculates the sum-time step deficit by:

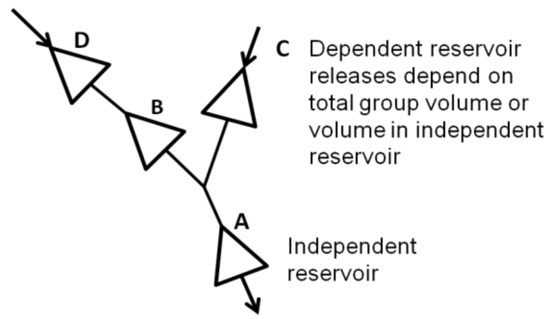
$$Deficit_{dn}^{st} = \frac{qTarget_{dn}^{t}}{tst} \tag{3.16}$$

If $Deficit_{dn}^{st}$ for any given node is greater than 0, then a supplemental release, $Release_{i,dem}$ [Mm^3] from demand source nodes is calculated according to

$$Release_{i,dem}^{st} = \sum_{1}^{\mathrm{dn}} \mathrm{x_i} * Deficit_{dn}^{st} \tag{3.17}$$

where i is the source reservoir node and $\mathrm{x_i}$ the deficit fraction. The supplemental release is a demand driven release target for reservoir i. Demand driven releases are denoted by the subscript '*dem*'.

After the demand-driven release calculation, supply driven releases are calculated using updated reservoir volumes considering demand driven releases. Group reservoirs use reservoir rules and balancing functions to determine their subtime step supply-driven releases whilst lakes use rating tables. Single reservoir releases use either the rule-based method or rating tables.



Total Storage Volume	Target Storage Volume in Reservoir A	B	C	D
10	5	0	5	0
20	10	0	10	0
60	30	5	20	5
100	30	25	25	20
200	30	45	60	65

Figure 3.3 Reservoir group with one independent reservoir (A) and three dependent reservoirs whose releases are controlled by a balance table (in user-defined volume units) giving the ideal storage level in each reservoir as a function of total group storage volumes. Adapted from Loucks et al. (1995).

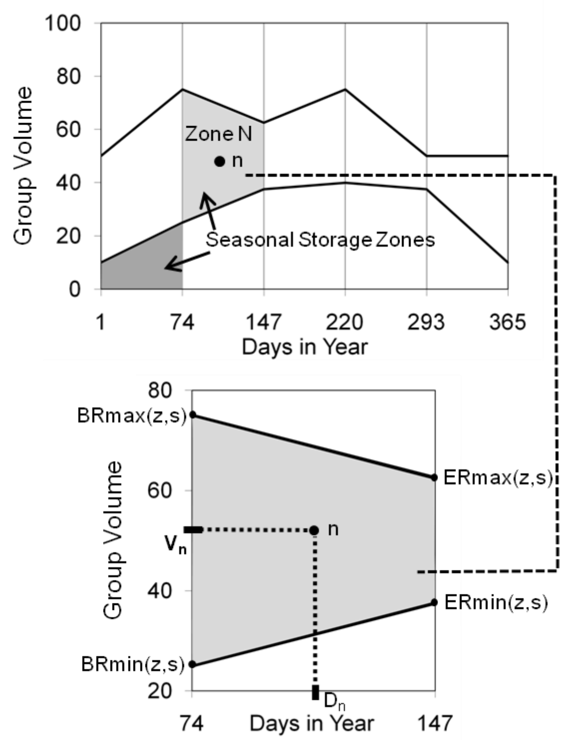


Figure 3.4 Reservoir release rule function for independent reservoirs in user defined volume units (e.g. reservoir A in Figure 3). Release rates are a function of total reservoir group storage and the day within the year. Rule release is calculated using linear interpolation between the release rates defined at the four corners of a seasonal zone (as seen for point n inside seasonal zone N). Adapted from Loucks et al. (1995).

An example reservoir group is seen in Figure 3.4. The independent reservoir in the group uses a reservoir rule function (Figure 3.4) to determine releases whilst the dependent reservoirs use balance functions to calculate release as a function of their own storage volumes and either the total group storage (first column in Figure 3.3) or the volume of the independent reservoir (second column) .

Reservoir rule tables are split into seasonal storage zones (Figure 3.4). Two such seasons can be seen in grey in Figure 3.4. Each season has unique release rates even if they are on the same point on the plot. Each corner has a corresponding rule release rate (not necessarily proportional to volume). For example, the corner shared between the two grey seasonal storage zones in the figure can have different release rates. Both the beginning and the end of the season(s) have a minimum and maximum release rate at the minimum and maximum storages of the zone (z) (BRmin(z,s), BRmax(z,s), ERmin(z,s), ERmax(z,s) respectively). Their release rates can be seen on the corners of zone N. Linear interpolation is used to find the rule release rate based on the seasonal zone, the day in the year and the total group volume. The releases interpolated from the release functions become the rule based output of the independent reservoir. This is seen in the figure where the rule release for point n interpolated at day D_n and group volume V_n in seasonal storage zone N.

Releases from dependent reservoirs occur when dependent reservoir volume is greater than the volume specified by the balance table. Abstraction to dependent reservoirs is not limited by balance tables as they can still refill passively. To limit managed abstraction, dependent reservoirs can be assigned a refill trigger which can prevent the reservoir from abstracting water from divergence nodes until the storage of the independent reservoir in the group reaches a certain level.

Reservoir supply-driven and demand-driven releases combined constitute target release. Target release may be modified subject to minimum and maximum release rates. Once storage releases are calculated, the effects of rainfall, evaporation and seepage on surface storage nodes are calculated.

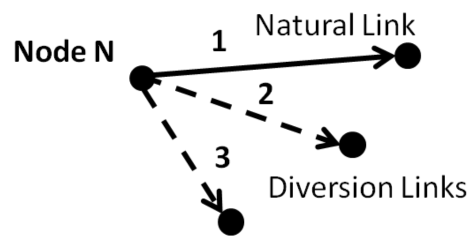
3.4.2 Loop II – Inflow and Outflow of Surface Nodes

Loop II calculates node inflows and outflows for all non-aquifer and non-wetland nodes. This is done by propagating natural flow and storage node releases downstream whilst obeying allocation rules on unidirectional links. Flow through bidirectional links connected to any node calculated in this loop is also calculated. Bidirectional links connecting two aquifers or wetlands are not calculated here.

The allocation calculation process proceeds by order of outgoing link type (outgoing links are those that exit the node, link types are described in Section 3.1.2). Allocation calculation order in outflow links of the same type follows input file declaration order. Allocations to bidirectional links are made first followed by consumption on the node itself (which is treated as an allocation) then allocations to demand links, diversion links and finally natural links. If there is not enough water to cover all allocations, lower priority network elements do not receive allocations.

Allocations to bidirectional links are calculated according to Equation (3.7) or user defined bidirectional flow tables. Consumption at nodes is a fixed proportion of available water. Demand links have an associated demand node either directly downstream or the link has been designated as the supply link of a demand node. In either case, subject to water availability, an amount equal to the demand node's previously described subtime step's deficit, $Deficit_{dn}^{st}$, is allocated. Allocation to demand links can be limited to a defined link flow capacity. Diversion links use functions similar to consumption functions. The water originally available (before demand and consumption allocations were performed) at the initial node of a diversion link is used to calculate the diversion amount. An example of diversion allocation functions can be seen in Figure 3.5. Diversion links can also have a limited flow capacity.

Once demand and diversion table allocations have taken place, any remaining water is distributed equally to all natural links. Natural links are links without a defined flow capacity. If a demand or diversion function link does not have a defined capacity it is also considered a natural link and more water can be allocated to it at this step. Return flows from a consumption node can be modelled as allocated flow to an outgoing link. Hydropower generation or pumping energy requirements and routing defined on links are calculated in this loop.



Node N Outlfow	Outflow Allocations to 1	2	3
0	0	0	0
10	10	0	0
30	10	5	15
50	10	20	20
90	45	25	20

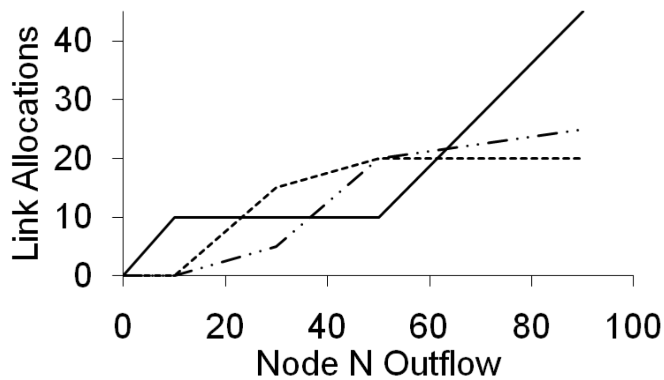


Figure 3.5 Diversion links and example table showing flow allocation to diversion links as a function of the total amount of water leaving node N. The plot below the table provides a visualisation of the diversion functions (in user defined flow units). Adapted from Loucks et al. (1995).

3.4.3 Loops III & IV – Remaining Bidirectional Link Flows

The third loop in the subtime step computes the remaining uncalculated flows including flows through bidirectional links connecting groundwater or wetland nodes and calculates pumping energy requirements. The fourth loop updates the aquifer and wetland node storages by taking into account the flow through bidirectional links.

This four-loop process is repeated for every subtime step of each time-step until the end of the simulation.

3.4.4 Summary of IRAS-2010 improvements

An understanding of the IRAS-2010 solution algorithm is useful to understand the changes introduced in this version. These are summarised below in Table 3.2.

Table 3.2 New developments in IRAS-2010 (item numbers correspond to those described in Section 3.1.1.)

(1)	There is an option to bypass the future sub-time step extrapolation algorithm to calculate the demand deficit for nodes that only receive diverted flow and no natural flow (no 'passive' water).
(2)	The demand link associated to a demand node no longer needs to be directly upstream of the node to request diversion to satisfy its deficit.
(3)	Reservoir groups can be balanced on either the total group storage or on only the lead reservoir's storage and refill triggers for dependent reservoirs can be set
(4)	Flow demand of demand nodes can be reduced depending on the storage of an associated reservoir to simulate demand restrictions in times of supply shortfall.
(5)	Flow demand can be set to increase annually by a user-defined percentage or a time-series of demand can be used to represent complex demand fluctuations.
(6)	For links that cannot use IRAS-2010's pumping energy or hydropower algorithms (e.g. desalination energy) energy requirements per unit of water can be defined. Energy prices can also be defined to calculate variable operating costs.
(7)	Darcy's equation can be used to simulate simplified inter-aquifer and aquifer-surface water interactions.
(8)	If routing is enabled, channel depth, width and flow velocity can be calculated.
(9)	An output file with several performance measures evaluated at storage and flow demand nodes, energy consumption and production as well as associated energy cost and revenue is generated at the end of the simulation.
(10)	Multiple runs using monthly flow factors to perturb flow time series is possible.
(11)	IRAS-2010 now uses text-based input files and supports leap years.

3.5 Thames Basin Application

To demonstrate the effectiveness of IRAS-2010, a model of the Thames water resource system (Figure 3.6) was built. Input data was obtained from an existing Thames water resource system model maintained by the Environment Agency (EA) of England and Wales. The EA's Thames model uses a water resource simulation software package developed for the UK water industry context named AQUATOR (Oxford Scientific Software, 2008). Both Thames models have similar spatial resolution and use a daily simulation time step over the historical time horizon (1920-2005). A schematic of the IRAS-2010 network as it appears in the current release of HydroPlatform is displayed in Figure 3.7.

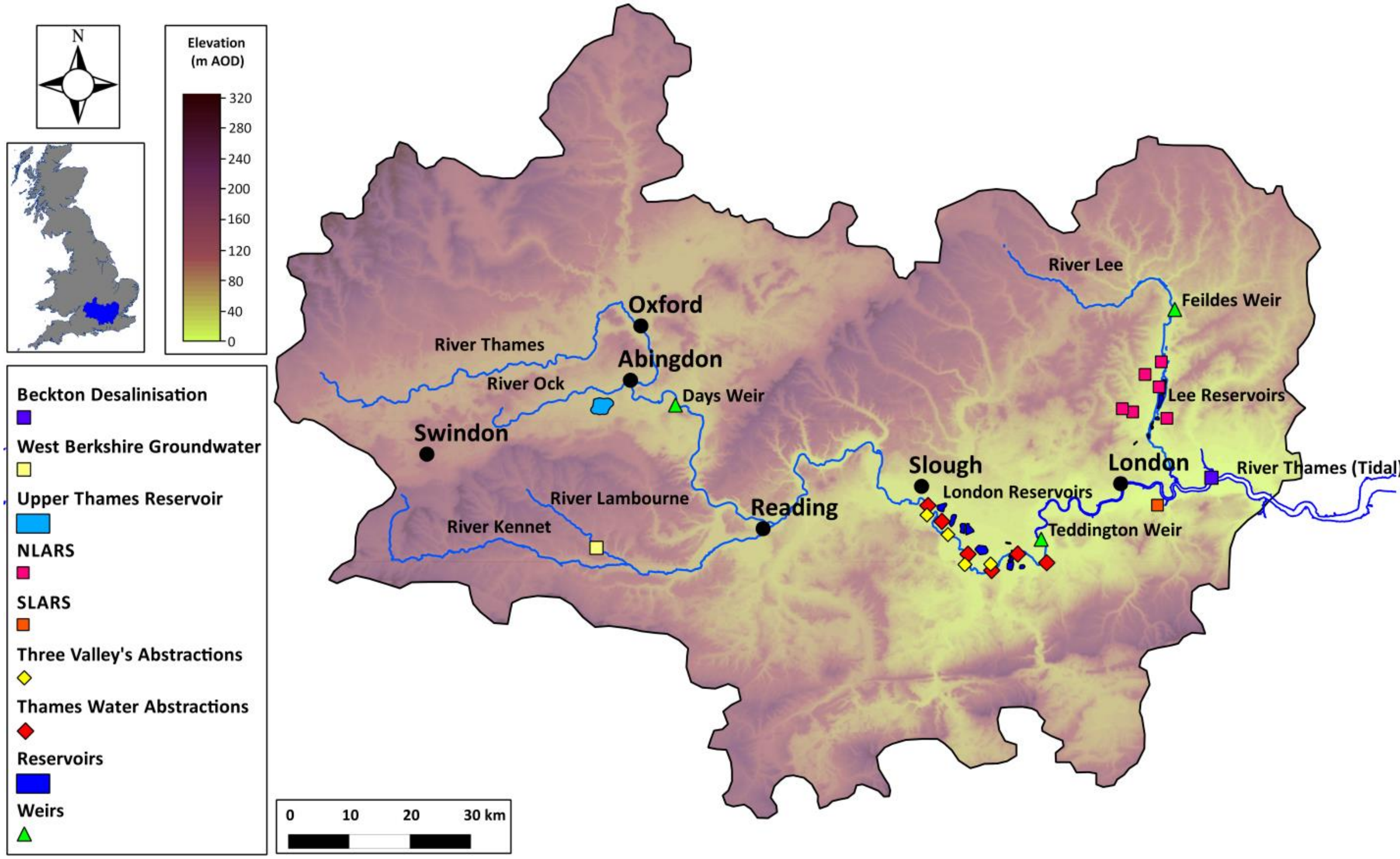


Figure 3.6 The Thames river basin featuring major urban centres with the river Thames and its main tributaries. Rivers originate in the highlands to the west and north. Thames Water and Veolia reservoirs are seen to the west of London and in the Lee valley. The UTR is seen to the south-west of Abingdon. The WGBW is found on the river Kennet in the south-west whilst NLARS is situated in the Lee valley and SLARS south-east of London. The desalination plant is located on the Thames estuary east of London.

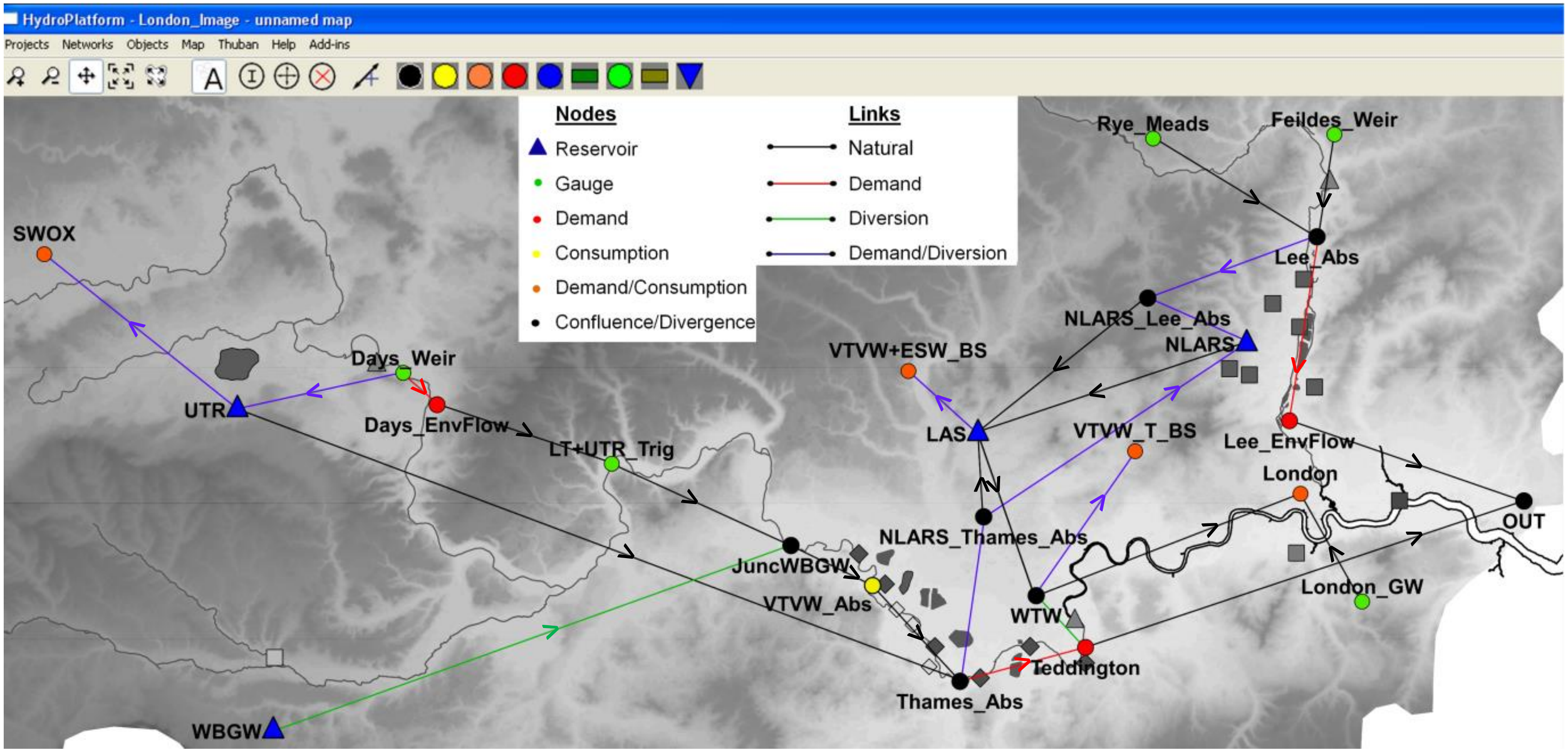


Figure 3.7 Thames IRAS-2010 model network in current HydroPlatform interface featuring 5 'gauge' nodes with time-series inflows (Days_Weir, LT+UTR_Trig, Feildes_Weir, Rye-Meads and London_GW), 5 flow 'consumption' and 'demand/consumption' nodes representing urban demand centres or bulk-supply (BS) transfers to other water companies (London, SWOX, VTVW_Abs, VTVW_T_BS, and VTVW+ESW_BS), and 3 minimum environmental flow 'demand' nodes (Days_EnvFlow, Lee_EnvFlow and Teddington). The Lee Valley and Thames reservoirs are aggregated into LAS. LAS and UTR are reservoir nodes and storage 'demand' nodes so that they abstract water when not full. Leakage from the aggregated Water Treatment Works (WTW) node is represented by a link connecting WTW to Teddington.

3.5.1 Thames Water Resource System

The River Thames is one of England's major rivers, and it provides about two thirds of London's water supply (Environment Agency, 2009). It flows eastward 346 kilometres to the North Sea through some of England's most urbanized areas including London. Over 13 million people live within its 16,133 km^2 catchment area. Surface water accounts for roughly 60% of water supplies and groundwater 40% in the Thames basin. The water supply is managed by two private water companies: Thames Water Utilities Limited (TWUL) and Veolia Three Valleys Water (VTVW). Thames Water owns thirteen reservoirs in the north-east of London by the Lee river and a group of reservoirs south-west of London supplied by the Thames. The two reservoir groups are connected via a bulk transfer from the Thames Reservoirs along the Thames-Lee Tunnel (Halrow Ltd., 2010). The River Thames provides over 50% of TWUL's supply and satisfies 70% of London's demand (Jones, 1983). The Thames basin has two conjunctive-use schemes. The North London Artificial Recharge Scheme (NLARS) recharges excess treated water to an aquifer for later use during dry periods. The West Berkshire Ground Water Scheme (WBGW) is available for intensive use during droughts. TWUL began operation of a desalination plant along a tidal stretch of the Thames in 2009.

3.5.2 Thames IRAS-2010 Model Components

3.5.2.1 Inflows

Surface water enters the system at Day's Weir on the River Thames and at Feildes Weir on the River Lee. Inflows are publically available daily historical flow rates obtained from the National River Flow Archive[1] (NFRA). London's groundwater use is modelled as an aggregate inflow into the London demand node. An aggregate inflow node called the Lower Thames represents the aggregate inflow into the Thames between Day's Weir and Teddington and is obtained by subtracting the daily historical flows at Teddington from those at node Day's Weir. This simplification produces negligible error because the small distance between the two nodes allows the routing of daily flows to be ignored.

3.5.2.2 Water Consumption Nodes

There are five consumption nodes representing regions that consume water. Some of these water demands vary on a monthly basis to simulate seasonal demand variations. All consumption nodes

[1] http://www.ceh.ac.uk/data/nrfa/index.html

are fed by surface storage with the exception of a Three Valleys Regional Abstraction which is supplied directly from the Thames and London Demand which is supplemented by groundwater. Demand reductions representing water use restrictions are triggered by the Lower Thames Control Diagram (LTCD) (Figure 3.8) when storage (levels 1 through 4) is low. Different storage levels of the LTCD determine environmental flows at Teddington (Figure 3.8).

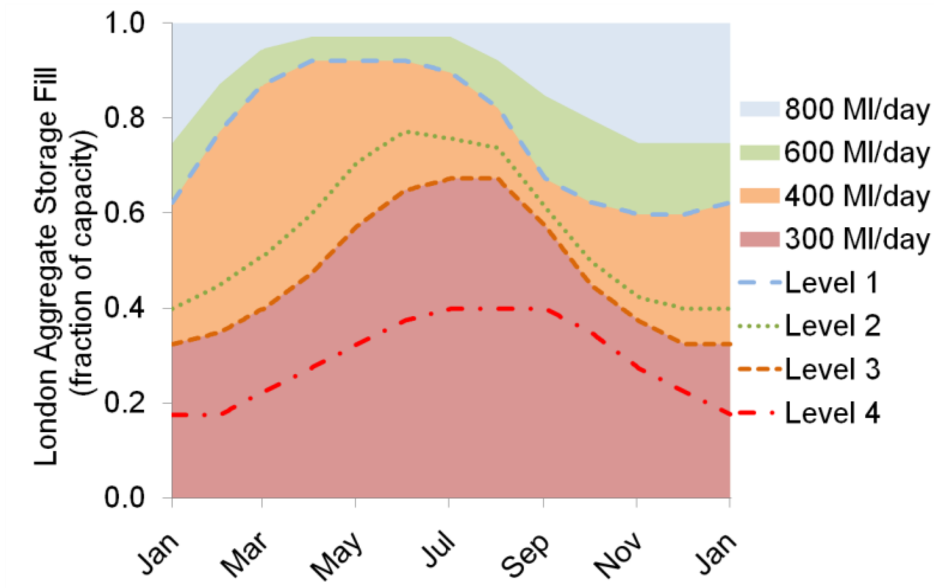


Figure 3.8 Lower Thames Control Diagram (LTCD) showing how London demand reduction thresholds (Lev 1 – Lev 4) and minimum environmental flow rates at Teddington are a function of London's aggregate storage reserves.

3.5.2.3 Storage Nodes

The 'London Aggregate Storage' (LAS) reservoir represents the London-area Thames and Lee River reservoirs. Water is diverted to LAS first from the Lee River and then from the Thames subject to downstream environmental minimum flows and maximum daily abstraction limitations. NLARS is connected directly to LAS and releases water when LAS level goes below the Teddington 800/600 Ml/day line seen in Figure 3.8. NLARS is refilled by abstractions from the links connecting to the LAS and limited to 40 Ml/day. In reality, NLARS is refilled using treated water from London's main distribution network. This water is supplied by the water treatment works which obtain water from the Lee and the Thames. Such an abstraction and refill system would require a loop flow where the LAS both receives and releases water to and from NLARS. This is impossible using IRAS-2010; instead NLARS abstracts water destined for LAS.

Because NLARS is closer to the Lee abstractions, diversion from the Thames to NLARS is limited to 35% of total abstraction. NLARS refills only when LAS is 99% full. Because NLARS is an engineered storage system it is modelled by both AQUATOR and IRAS-2010 as a reservoir even though it is an aquifer storage. WBGW is also modelled as a reservoir with a maximum storage with an inflow time-series representing natural recharge. Its release to the Thames is activated when LAS goes below the Level 2 line (Figure 3.8).

The IRAS-2010 model includes the proposed Upper Thames Reservoir (UTR). The UTR supplies water to a consumption site and to the Thames when activated. Release to the Thames is activated when flow downstream goes below 3000 Ml/day. UTR Thames abstraction is limited by a downstream minimum environmental flow and a daily abstraction limit.

3.5.2.4 Water Treatment Works

Water Treatment Works (WTW) are modelled as a divergence node that feed the London demand node and a demand node representing a water transfer to another water company. A part of WTW inflows leaks out into the environment during treatment. Most of this leakage makes its way through seepage to the Thames as most of the WTWs are located near the river. This seepage is modelled as a link into Teddington and contributes to Teddington's minimum environmental flow. Some WTW are located near the Lee and do not contribute to Teddington's flow. This part of the leakage is modelled as losses from this link.

3.5.2.5 Teddington

Teddington weir has a minimum environmental flow between 300 and 800 Ml/day set by the LTCD which limits abstraction from the Thames.

3.5.3 Brief description of the AQUATOR Thames model

The AQUATOR Thames basin model follows the same physical network topology as the IRAS-2010 model and runs on a daily time-step over the same 85-year time horizon. Both models use the same inflow time-series. In general all model components follow the same operating rules with the exception of those that use custom scripting in the AQUATOR model.

AQUATOR allows custom scripting of individual network elements which provides a level of customisation not available in the procedural IRAS-2010 code. AQUATOR uses custom scripting to allow both NLARS and LAS to release water to one another. AQUATOR's scripting also allows UTR to abstract from the Thames only when UTR is not releasing water, but this had little effect on the model since a minimum environmental flow downstream of the abstraction served as the main abstraction limit. In the AQUATOR Thames model the WBGW refills instantaneously once LAS reaches its full capacity whilst in IRAS-2010 it is refilled with a more realistic daily inflow.

3.6 IRAS-2010 Calibration Results

IRAS-2010 results are compared with AQUATOR results and historical gauged river flows (from NFRA) when possible. Historical data on managed flows, abstractions and storages are not in the public domain in England and Wales which means for example that historical and modelled reservoir use cannot be compared. Therefore IRAS-2010 results are compared to those calculated by an AQUATOR Thames model built by EA regulators who are familiar with the system's operation.

LAS over an 85-year period is displayed in Figure 3.9. IRAS-2010 and AQUATOR show similar storage levels except for drought periods when LAS levels went lower in AQUATOR than in IRAS-2010. These discrepancies are a result of small differences in storage levels in LAS at the beginning of the droughts in the two models putting LAS storage on different points on the LTCD in each model. This results in demand reductions going into effect at different times and also affects the timing of NLARS and WBGW activation resulting in growing discrepancies in the LAS storage during the drought. The inset in Figure 3.9 shows storage differences are minor during the years 1943-1945.

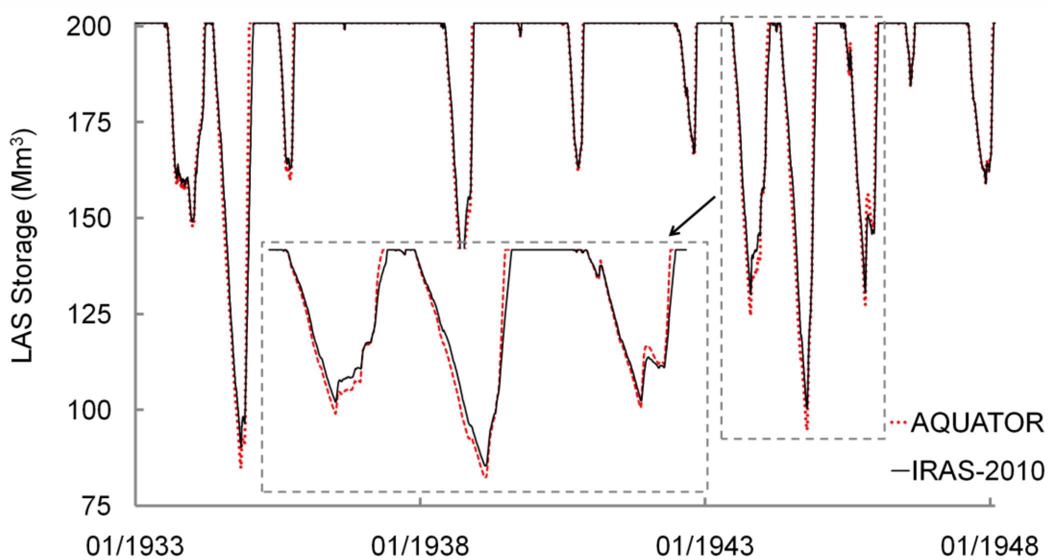


Figure 3.9 London Aggregate Storage (LAS) simulated by the IRAS-2010 and AQUATOR models.

Figure 3.10 shows London consumption results for a three-year period including a dry spell between 1921-1922. During this drought demand reductions were activated and demand is compared to normal demands.

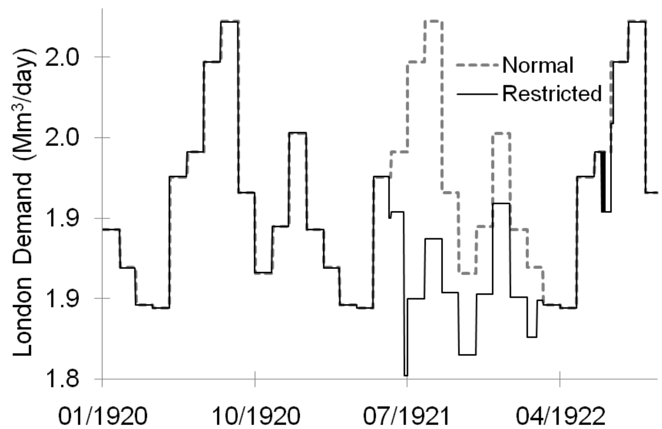


Figure 3.10 London demand during a drought event compared to normal demand levels as modelled by IRAS-2010.

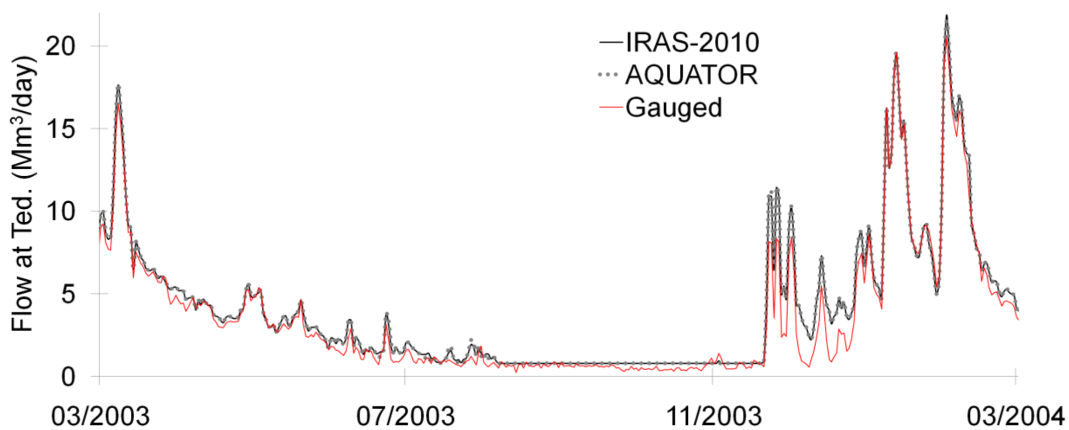


Figure 3.11 Flow rates at Teddington (Ted.) calculated by IRAS-2010 and AQUATOR plotted against gauged flows.

Figure 3.11 shows flow at Teddington weir after all Thames abstractions have been made and after additions from the WTW. Abstraction to LAS directly upstream of this node is limited by the minimum environmental flow at Teddington which is dictated by the LTCD. AQUATOR and IRAS-2010 show the same flows through Teddington but show discrepancies with historical flows (obtained from NRFA). Given the simplifications of these screening models including lack of routing and stream-aquifer interaction these results are deemed satisfactory. Both models show that during late 2003 only the minimum environmental flow was left in Teddington. This is mirrored in the historical flow time-series, albeit with some noise.

Figure 3.12 a shows a strong correlation between IRAS-2010 Teddington flow rates and historical flows.

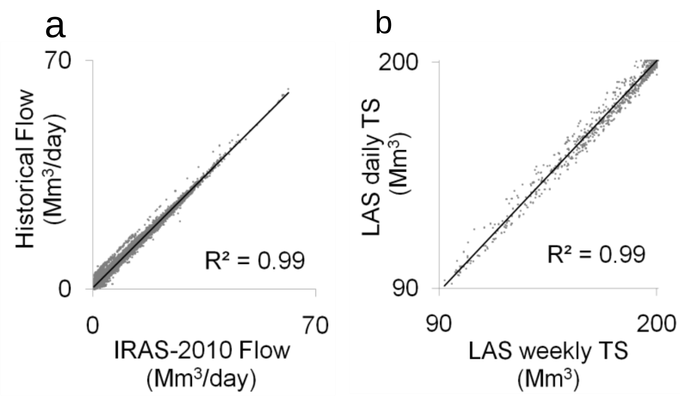


Figure 3.12 Teddington historical and IRAS-2010 flow correlation (a) and Weekly and Daily Time Step (TS) correlation plot for LAS (b).

Pumping energy consumed during abstraction from NLARS during a drought event is displayed in Figure 3.13. As groundwater levels drop more energy is required.

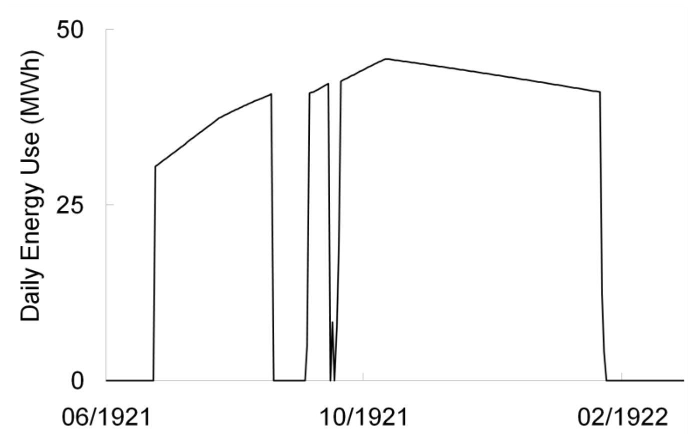


Figure 3.13 Pumping energy use from NLARS conjunctive use scheme during the drought between 1921-1922.

3.6.1 IRAS-2010 Weekly Model

The IRAS-2010 Thames Basin model was run with a weekly time step to investigate how a coarser time step affects results (e.g. if a large deviation between the storage or flow time-series produced by the daily and weekly time-step simulations appears). The weekly time step and bi-weekly LTCD step function approximation reduced run-time to roughly 1 second on a 2 GHz desktop compared to 15 seconds for the daily time step and daily LTCD version. The correlation plot (Figure 3.12 b) comparing storage under the daily and weekly time-steps shows the coarser time-step closely resembles daily results. The highest density of deviation between the two models occurs when the LAS is nearly full. This is a result of a subtime step lag that will be discussed in the next section.

3.7 Discussion

3.7.1 Limitations of the IRAS-2010 model

Although IRAS-2010 closely emulates the EA's AQUATOR model results, limitations do exist. IRAS-2010 lacks scripting capabilities that would allow users to customize individual network object behaviour. Lack of scripting increases ease of use but it also means some complex relationships between model components are more difficult to represent. In procedural programs like IRAS-2010, such special behaviour needs to be programmed into the standard subroutines used for all nodes. Some features scripted in the AQUATOR model could be programmed into IRAS-2010 subroutines but they would not be as flexible.

IRAS-2010 currently has no direct way to define which storage node or link serves as a higher priority contributor to a demand node. The order in which links connecting to a demand node are defined in IRAS-2010 sets the priority in most but not all instances. Higher priority links contribute the greatest part to a demand node, but some water is still drawn from lower priority links. This happens in the Thames IRAS-2010 model when some water is taken from the Thames even though the Lee could have satisfied the LAS storage deficit.

Another minor current limitation occurs when a reservoir provides significant flow to a downstream flow demand node. The subtime step lag in the demand deficit calculation means at the end of a time step reservoir volume is missing roughly one subtime step release equivalent. This limitation becomes less apparent with smaller subtime steps. This and other known minor computational issues will likely be corrected or mitigated over time.

3.7.2 Benefits of the IRAS-2010 model

Despite these limitations the flow time-series produced by the IRAS-2010 Thames model compares well to gauged Thames flows at Teddington weir and the model closely emulates flows estimated by an existing calibrated system model used by regulators. IRAS-2010 is straight forward to configure and use, and requires no advanced scripting skills. The availability of a separate customisable open-source user-interface (HydroPlatform) is useful to those who would want to customise a decision support system (DSS) for a particular IRAS-2010 model.

IRAS-2010 is computationally efficient making it an attractive model for planning methods that require multiple runs or for collaborative workshops where participants want quick feedback on effects of proposed system changes. The IRAS-2010 Thames model using a weekly time step over an 85 year time horizon runs in roughly 1 second on a 2 GHz computer. The user-selected time step and ability to implement hydrological routing increase the tool's flexibility. The use of multiplicative flow factors is useful for climate change studies which typically multiply historical flows by perturbation factors meant to represent possible climate change. IRAS-2010 can easily be run by wrapper codes that automate multiple runs by modifying IRAS-2010's input files.

3.8 Conclusions

IRAS-2010 is an effective computationally efficient generalised open-source computer program to simulate water resource systems. IRAS-2010 estimates flow and storage of water in natural (rivers, lakes, wetlands, aquifers) and engineered (reservoirs, canals, water abstractions, consumptive use, hydropower, etc.) water resource systems. It tracks flows, storages, water supply status, operating costs, energy production and use, and environmental performance throughout the network at each time-step.

An application to the Thames River and London's conjunctive use water supply system shows IRAS-2010 closely emulates a water resource simulation model maintained by the Environment Agency of England and Wales. Relatively little information was lost in the transition from a daily to a weekly time-step. The weekly time-step simulation was shown to be a quick and accurate screening tool. IRAS-2010's main limitation as a procedural code is that all model behaviour must be programmed into general source code subroutines; customising the behaviour of specific network elements using a scripting language is not possible. Its computational efficiency makes it appropriate for stochastic applications, where many model runs are required, or for interactive use in a workshop context. Promising fields of application include climate change impact and adaptation studies and modelling with stakeholders. IRAS-2010 is free and open-source software package allowing the water management modelling community to further diversify its subroutines, improve performance, and identify and fix errors. In the following chapters the IRAS-2010 water resource simulator is incorporated in state-of-the art planning methods.

4 Robust Decision Making Method

4.1 Introduction

In planning water supply and the general management of water resource systems uncertainty in future conditions poses a major problem. The uncertainty is due both to stochasticity (which can be described by probability distributions) and Knightian uncertainty (Knight, 1921), more recently referred to as 'deep' (Lempert et al., 2006b) or 'severe' (Ben-Haim, 2006) uncertainty, when the probability distributions describing future conditions are unknown (see also Section 2.1) . When planning is performed under such circumstances, planners may seek robust solutions. A robust solution is one that performs well under a wide range of possible future conditions rather than optimally in a few.

Robust Decision Making (RDM) (Lempert et al., 2003) is a decision making framework that seeks robustness rather than optimality. RDM provides a structured approach to planning complex systems under 'deep' uncertainty. The framework makes repeated use of trusted simulation models to evaluate different plans under different future conditions (scenarios) and then uses a statistical cluster finding algorithm to identify the strategies' vulnerabilities. RDM is reviewed in depth in Section 2.2.

This chapter provides two applications of RDM to a water resource system planning problem on the Thames basin. Both applications seek to find the most robust Thames water supply strategy for the year 2035. Uncertainties considered include future hydrological inflows, water demands and energy prices. Robustness in reliability of water supply service, maximum reservoir storage deficit, environmental performance, energy consumption and total costs (capital and operating) is considered.

The first application considers only supply additions to the current system and includes a possible new reservoir, a groundwater-surface water conjunctive use scheme and running a new desalination plant at two possible capacities. All together 20 proposed water supply portfolios are considered. The second application includes the same supply options but additionally considers demand management options including leakage control, metering properties, implementing seasonal tariffs and water efficiency improvements. This second problem considers 240 total unique portfolios.

4.2 Case study: London water supply planning

This study focuses on water supply source selection in the Thames basin of Southeast England (Figure 4.1) considering demand levels projected for the year 2035. The basin (16,000 km^2) has over 12.5 million inhabitants and contains important cities including London. The Environment Agency (EA) considers the region to be seriously water stressed. Only Cyprus, Malta, Spain and Italy abstract proportionally more freshwater resources in Europe. Parts of the basin are over-abstracted damaging the environment during low flow events (Environment Agency, 2008b). The region has experienced six major droughts in the last 90 years (Marsh et al., 2007). Water stresses are expected to worsen resulting from an increase in demand and a decrease in supply resulting from climate change (Christierson et al., 2012; Sanderson et al., 2012). The population is estimated to increase by 2 million by 2026 (WWF-UK, 2008) whilst average household water use is expected to remain the same (~150 l/person/day).

A combination of infrastructure expansion and demand management is likely necessary to maintain the supply-demand balance in the Thames basin. In their Water Resources Management Plan (Thames Water, 2010), Thames Water outlines various plausible supply and demand management options.

4.3 Supply option infrastructure expansion study using RDM on the Thames basin

4.3.1 IRAS-2010 simulation model of the Thames basin

Applying the RDM framework requires a simulation model to estimate the performance of proposed supply and demand management portfolios (hereafter referred to as ‘portfolios’). An expanded version of the Thames Basin water resource system model described in Chapter 3 is used. The IRAS-2010 model focuses on the River Thames and Thames Water Utilities Limited’s (TWUL’s) London water resource zone (WRZ). A WRZ is a zone consisting of an interconnected subsystem whose residents have the same likelihood of experiencing a supply deficit. WRZs that receive abstractions from the Thames or transfers from the region include Veolia Three Valleys Water’s (VTVW) Central and Southern WRZs and Essex and Suffolk Water’s (ESW) Essex WRZ. Essex and Suffolk Water is a water company that that provides water services outside of the study area, but receives a transfer from TWUL.

The five demands of equal priority in the model include TWUL's supply to London (1934 Ml/day), aggregate raw water abstractions from the Thames by VTVW (VTVW_Abs) (405 Ml/day), aggregation of two raw bulk supply transfers of 10 and 91 Ml/day (VTVW+ESW_BS), bulk transfer of 10 Ml/day of treated water to VTV (VTVW_T_BS), and supply to the SWOX WRZ (24 or 48 Ml/day depending on the capacity of a future reservoir).

The model was expanded by adding potential supply and demand options that are described later in this chapter. The basin with the possible supply options can be seen in Figure 4.1. Supply additions include the Upper Thames Reservoir, the South London Artificial Recharge Scheme, the Beckton desalination plant and the River Severn Transfer. Demand options (leakage reduction, water efficiency measures and metering) are modelled as gauge nodes (inflow) that provide water directly into the system and are not represented in the figures.

Table 4.1 Important nodes in the IRAS-2010 model.

Node	Description
LAS	Aggregate system surface storage
Teddington	Gauging station downstream of all the Thames abstractions
London	Demand node representing TW's distribution input for London (1934 Ml/day)
VTVW_Abs	Demand node representing aggregate raw water abstractions from the Thames by VTV (405 Ml/day)
VTVW+ESW_BS	Demand node representing aggregation of two raw bulk supply transfers of 10 and 91 Ml/day
VTVW_T_BS	Demand node representing treated bulk supply to VTV
SWOX	Demand node representing supply to the SWOX WRZ (24 or 48 Ml/day depending on capacity of a future reservoir)

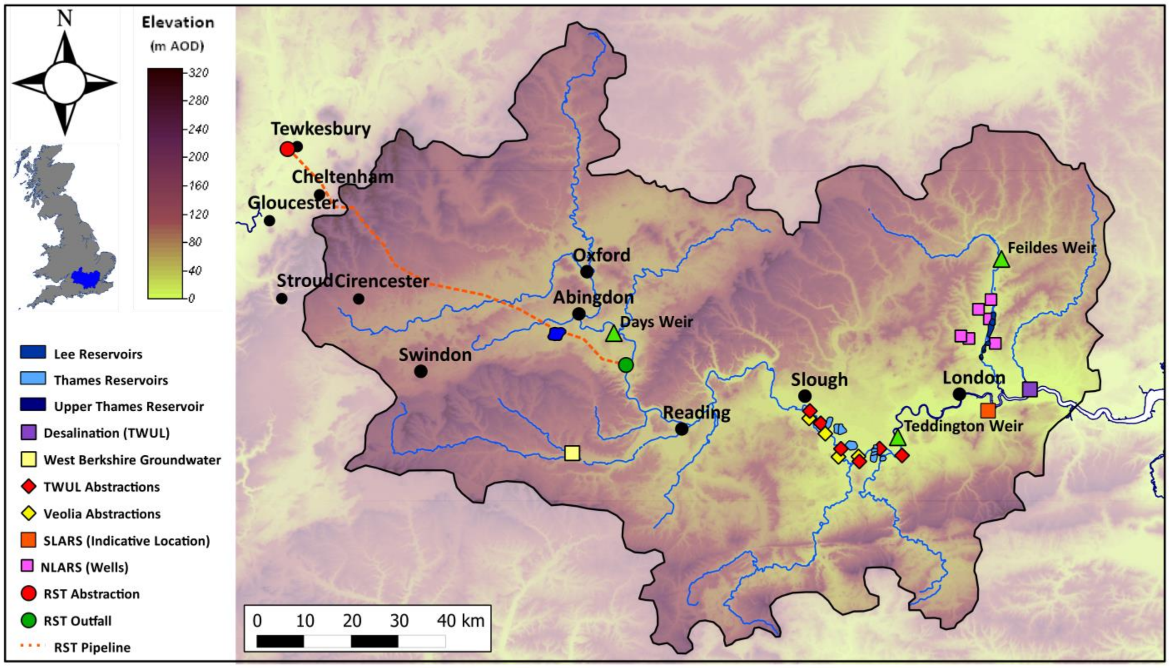


Figure 4.1 The Thames basin showing additional supply options including the Upper Thames Reservoir, the South London Artificial Recharge Scheme, the Beckton desalination plant and the River Severn Transfer. Adapted from Matrosov et al. (2011).

4.3.2 Problem formulation

In their latest Water Resource Management Plan (WRMP), Thames Water Utilities Limited (TWUL) describes 37 plausible future water supply options including multiple variants of the same option (Thames Water, 2010). Of these six options were selected, leading to 19 possible infrastructure portfolios (IPs) (unique combinations of supply options). Selection criteria included size of options (larger supply operations were preferred) and their feasibility as described in the water company management plans. Adding the current arrangement led to the 20 possible IPs, or 'options', considered in this case study (Table 4.2).

In the following the Upper Thames Reservoir (UTR) with capacities of 75, 100 or 150 million m^3 (Mm^3) (UTR75, UTR100, UTR150), the River Severn Transfer (RST) and the South London Artificial Recharge Scheme (SLARS) are investigated. The operation of the desalination plant at 80 Ml/day (DESAL80) and 140 Ml/day (DESAL140) are also analysed. Supply options are summarised in Table 4.3.

Table 4.2 The 20 water supply 'infrastructure portfolios' (IPs), alternatively called 'options' or 'plans' evaluated in the case study.

Infrastructure Portfolio	Future Supply Options
1	DESAL80
2	DESAL80, SLARS
3	DESAL140
4	DESAL140, SLARS
5	UTR75, DESAL80
6	UTR75. DESAL80, SLARS
7	UTR75, DESAL140
8	UTR75,DESAL140, SLARS
9	UTR100, DESAL80
10	UTR100. DESAL80, SLARS
11	UTR100, DESAL140
12	UTR100,DESAL140, SLARS
13	UTR150, DESAL80
14	UTR150. DESAL80, SLARS
15	UTR150, DESAL140
16	UTR150,DESAL140, SLARS
17	RST, DESAL80
18	RST ,DESAL80, SLARS
19	RST, DESAL140
20	RST,DESAL140, SLARS

All infrastructure additions incur capital costs except for the desalination plant which is already built to operate to a maximum capacity of 150 Ml/day. Variable and fixed operating costs are considered for each proposed option.

Variable operating costs are calculated by multiplying flow from supply nodes by the unit energy consumption, and unit energy cost. Energy consumption results from desalination and from pumping groundwater, to overcome elevation gain and friction loses in the RST, and to from the River Thames to the UTR and Thames Estuary to the desalination plant. A pumping efficiency of 75% (Ofwat, 2010) and a consumption of 2 kWh/m^3 for desalination of brackish water (Raluy et al., 2005a; Raluy et al., 2005b; Stokes and Horvath, 2006) are assumed. Table 4.4 summerises the costs, release rates and energy consumption of each of the possible supply options. Fixed and variable operating costs are also incurred by existing supply infrastructure such as NLARS and the Westberkshire Groundwater Scheme (WBGW).

Table 4.3 The seven possible future options considered in the study including one reservoir with varying capacities, a water transfer, a conjunctive use scheme and running the existing desalination plant at two different capacities (as seen in Table 4.2).

ID	Name	Description	Capacity
UTR75	Upper Thames Reservoir	High capacity reservoir to supply Swindon and Oxford (SWOX) and London. Daily maximum supply set to 157.5Ml/d[1].	75 Mm^3
UTR100	Upper Thames Reservoir	High capacity reservoir to supply Swindon and Oxford (SWOX) and London. Daily maximum supply set to 202Ml/d[1].	100 Mm^3
UTR150	Upper Thames Reservoir	High capacity reservoir to supply Swindon and Oxford (SWOX) and London. Daily maximum supply set to 315Ml/d[1].	150 Mm^3
RST	River Severn Transfer	High capacity bulk transfer of freshwater from the River Severn to the River Thames[1].	315 Ml/d
DESAL80	London Desalination	Reverse osmosis desalination plant	80 Ml/d
DESAL140	London Desalination	Reverse osmosis desalination plant.	140 Ml/d
SLARS	South London Artificial Recharge Scheme	Artificial groundwater storage and recovery scheme (South London) [1] (Figure 1).	22 Ml/d

[1](Thames Water, 2010)

Table 4.4 Costs and release rates of the management options.

Management Option	Release Rate (ML/day)	Capital Costs (M£)	Energy Use (kWh/m^3)	Fixed Operating Costs (k£/yr)
UTR75	133.5 to Thames 24 to SWOX[1]	536.9[1]	0.11[2]	360[5]
UTR100	178 to Thames 24 to SWOX[1]	725.5[1]	0.11[2]	370[5]
UTR150	267 to Thames 48 to SWOX[1]	821.6[1]	0.11[2]	380 [5]
RST	267 to Thames 48 to SWOX[1]	579.6[2]	1.08[2,3]	7,000[3]
SLARS	22[1]	2.3[2]	0.23[2]	53[5]
DESAL80	80	-	2.15[2,4]	830[5]
DESAL140	140	-	2.15[2,4]	930[5]

[1](Thames Water, 2010) [2]Potential energy equation with 75% pump efficiency [3](Ofwat, 2010)
[4](Raluy et al., 2005a; Raluy et al., 2005b) [5](Environment Agency, 2010)

4.3.2.1 Uncertainties

Uncertainties considered in this study include natural hydrological variation, climate change perturbation of natural hydrology, projected London water demand and future energy prices up to a 2035 planning horizon.

4.3.2.1.1 Natural Hydrological Variability

Significant flow variability has been observed on the River Thames since records began in the 1880s, including several periods of prolonged drought (Cole and Marsh, 2006; Marsh et al., 2007). To consider natural hydrological variability each IRAS-2010 Thames simulation is run over the 85-year historical period (1920-2005) assuming any one of these hydrological years could occur in 2035.

4.3.2.1.2 Climate Change Perturbation

Climate change uncertainty is represented using monthly climate change perturbation factors that are multiplied by historical river flow time series to estimate future flows. Perturbation factors based on UKCP09 probabilistic climate change projections (Murphy et al., 2009) were used to create sets of twelve monthly flow factors (UKWIR, 2009) valid for 2035. Each set of monthly flow factors represents one hydrological future.

The UKCP09 climate projections were developed by the UK Met office and are based on "perturbed physics" and multimodel ensembles produced by a variant of the HadCM3 climate model (Johns et al., 2003) and the results of 13 other Global Circulation Models (GCMs). Murphy et al. (2007) provide a description of multimodel and perturbed physics ensembles. The projections are based on the B1, A1B, A1F1 emissions found in the IPCC's (Intergovernmental Panel on Climate Change) Special Report on Emissions Scenarios (SRES) (Nakicenovic and Swart, 2000). Please consult Murphy et al. (2009) for a detailed description of the UKCP09 projections.

The Thames catchment was simulated using the Probability Distributed Model (PDM) (Moore, 1985) and the Catchmod (Wilby et al., 1994) rainfall run-off models using Latin Hypercube Sampling of the UKCP09 projections for the A1B scenario. A large number of modelled river flow times-series was generated representing the future and historical time periods to take into account uncertainty in hydrological parameters using the Generalized Likelihood Uncertainty Estimation (GLUE) methodology (Beven, 2006; Beven and Binley, 1992). Models that closely reproduced the historical time series were used to generate a distribution of monthly flow factors. Please see Christierson et al. (2012) for a detailed description of the flow perturbation factors.

An ensemble of 100 equiprobable flow factor sets was used. The flow factor sets were classified by their percentage perturbation effect on winter (November-April) and summer (March-October) historical flows. Climate perturbed winter hydrology ranged from 43% drier to 31% wetter whilst summers ranged from 41% drier to 20% wetter.

Limitations to using flow factors to represent uncertainty in hydrology do exist. The flow perturbation factors are applied to the historical flow time-series and do not take into account possible shifts in the hydrologic regime resulting from climate change. Furthermore, because the historical time series is used, only those droughts that are present in the historical time series are considered (after being perturbed using flow factors); the duration and frequency of droughts however does not change.

4.3.2.1.3 London Water Demand

London mean annual water demand estimates for the time horizon were obtained from TWUL's stochastic water demand forecasting tool (Thames Water, 2010) which are shown in Figure 4.2a. TWUL provided estimated future demand values with their corresponding probabilities but not the probability function from which they were derived. The demand projections for 2035 were then fitted to a gamma distribution using Matlab with shape 311 and scale 6.9 whose cumulative distribution and probability density functions can be seen in Figure 4.2a and Figure 4.2b respectively.

Nine levels of London water demand were obtained from deciles of the gamma distribution. Including the demand values at the 0.01 and 0.99 percentile of the gamma distribution raised the total demand values considered to 11.

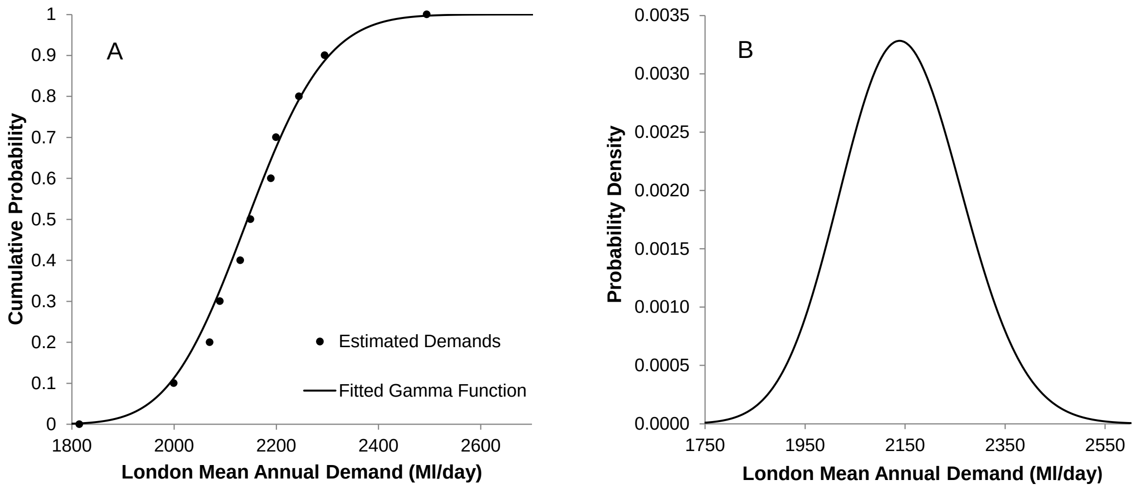


Figure 4.2 Thames water estimated demand points fitted to a gamma cumulative distribution probability function (a) and the corresponding probability distribution function (b).

4.3.2.1.4 Energy Prices

A uniform distribution of price estimates (£0.09- £0.22/kWh) was assumed based on current energy price (£0.09) assuming prices will increase (Eurostat, 2011). The uniform distribution was divided into 13 equiprobable intervals whose boundaries were used to produce 14 energy costs. Uncertainties are summarised in Table 4.5.

Table 4.5 Uncertain system parameters for strategic water resource forecasting in the Thames Basin for the 2020-2035 planning horizon.

Parameter	**Description**
Hydrological Variability	Historical flows[1]
Climate Change Perturbation	100 monthly flow perturbation sets valid for 2020-2035[2] (Monte-Carlo sampling)
Water Demand	11 water demand levels obtained using LHC sampling of deciles of a gamma distribution + 2 extreme values from distribution forecasts [3]
Energy Prices	14 energy prices [4] obtained using LHC sampling of 13-quantiles of a uniform distribution

[1]NRFA [2](UKWIR, 2009) [3] (Thames Water, 2010) [4] (Eurostat, 2011)

4.3.2.2 Performance criteria

RDM requires performance criteria to classify each simulation as a failure or success. Success or failure is based on five satisficing (Simon, 1959) and Section 2.2) metrics: reliability of water supply service, maximum reservoir storage deficit, environmental performance, energy consumption and total costs (capital and operating). These five criteria were chosen as they represent a selection of possible stakeholder interests (described below) that may conflict. (e.g. better supply reliability and environmental performance can result in increased costs).

The service reliability criterion is based on the frequency of water use restrictions imposed in the Thames basin over the full simulation. The service reliability criterion may be of interest to the water price regulating body (Ofwat) that requires that water companies provide a minimum level of service and also the water users which pay for water services. The restrictions considered are water use restriction levels 2 (L2) and 3 (L3) from the LTCD (Figure 3.8) which correspond to sprinkler and hosepipe/non-essential use ban respectively. Average service reliability is based on an occurrence reliability (based on Equation (1.1) by assessing the number of weeks (W_{fail}) each restriction level (i) was imposed in the simulation over the whole 85-year simulation (W_{sim}) :

$$R_i = \left(1 - \frac{W_{fail,i}}{W_{sim}}\right) \tag{4.1}$$

Thresholds for L2 and L3 failures were calculated from the current maximum frequency of supply restrictions Thames Water will impose; 1 in 10 years for sprinkler bans (level 2 – L2) and 1 in 20 years for hosepipe/non-essential use bans (level 3 – L3). For L2 restrictions the 9 month (40 week) sprinkler ban imposed by Thames Water in 2007 (BBC, 2007) is used as a representative L2 restriction duration. An allowable frequency of L2 restrictions of 1 in 10 years translates to 332 weeks of allowed L2 restrictions over the 85-year simulation (40 weeks x 85 years/10 years = 340 allowed failure weeks). L3 restrictions can be imposed no more frequently than 1 in 20 years (half that of level 2) and a representative failure duration of 4.5 months (340/2 = 170 allowed failure weeks) is used in line with historical durations of non-essential use bans in southeast England (WaterBriefing, 2006). Following Equation (4.1) with a total 4533 weeks in the simulation time horizon, a reliability of 0.925 for restriction L2 (sprinkler ban) is used for this study and a reliability of 0.973 is used for restrictions at L3.

The storage susceptibility metric is defined as the lowest storage level reached by LAS. Its emergency storage of 22.5% of capacity (45 Mm^3) is the threshold below which failure occurs due to pressure-related distribution problems in the network (Cookson and Weston, 2008). This engineering performance criterion may be of interest to the water company to know how susceptible the system is to the effects of climate change.

Environmental performance is calculated downstream of the last abstraction on the Thames at Teddington Weir. A failure occurs whenever the flow at this node drops below 800 Ml/day, the minimum environmental flow during normal conditions (Figure 3.8). The environmental performance criteria may be of interest to environmental regulatory bodies such as the Environment Agency which regulate water abstractions. The duration and severity of these failures are quantified using the Shortage Index (*SI)* adapted from Fredrich (1975) and Hsu et al. (2008) and based on Equation (1.8):

$$SI = \frac{100}{N_T}\sum_{t=1}^{N_T}\left(\frac{WS_t}{WD_t}\right)^2 \tag{4.2}$$

where WS_t is the flow shortage at week t, WD_t is the weekly flow minimum (800 Ml/day x 7 days) and N_T is the total weeks in the simulation. Higher SI values signal worse performance.

The energy consumption criterion is the total cumulative energy consumed by infrastructure during each simulation run. The total cost criterion combines capital and cumulative operating costs of each simulation. The costs and energy criteria are of interest to water companies who build and operate the water resource system and the regulatory body (Ofwat) which sets water price limits based on water company investment and operating costs. Capital costs, fixed operating costs and energy consumption figures for infrastructure options are provided in Table 4.4. Because in effect only the year 2035 is modelled, costs are not discounted.

Because of a lack of explicit performance requirements for the environmental, energy and cost criteria the worst 15% of performances are considered to be failures. The 15% percent failure threshold was selected as it resulted in a similar amount of failures in each criterion as compared to the other metrics to avoid biasing system failure to a single criterion. In the RDM and Info-gap implementations, if a simulation fails in at least one of the performance criteria outlined above, that particular simulation is considered a failure.

These performance metrics are considered sufficient to illustrate this RDM study. Water resource systems are complex and other and more complex metrics can be used but are beyond the scope of this study. Additionally, other case studies may require different metrics not discussed here..

4.3.3 RDM Implementation

From among the twenty possible infrastructure portfolios (IPs) one is selected as the candidate strategy. Its vulnerability scenarios are then identified and it is determined which IP would perform better inside these scenarios to consider possible trade-offs between IPs. Ways to address weaknesses in the IPs are considered.

A full enumeration of 20 IPs (Table 4.2), 101 climate perturbed flow time-series (100 equiprobable hydrological realisations and the historical record), 11 levels of estimated London water demand and 14 values of energy costs described in Section 4.3.2.1 leads to 311,080 simulations.

4.3.3.1 Choosing a candidate strategy using regret analysis

For RDM one of the twenty IPs must be selected as the initial candidate strategy. A regret-based ranking (Savage, 1954) of the proposed IPs is performed to identify which IP performs best over the simulated set of plausible futures.

Regret, or deviation from an ideal performance of criteria *c*, is the difference in the performance *P* of the best performing strategy (*s'*) and that of the strategy in question, *s*, for the same input parameters, *j*.

$$R_c(s,j) = |P_c(s',j) - P_c(s,j)| \tag{4.3}$$

For cost, energy and the environmental shortage index; where low values are better, an absolute value is required. In addition to considering regret for each criterion, multi-criteria regret, where the regrets are standardised over a 0 to 1 interval and weighted equally is also considered.

Four performance criteria are used to determine the overall performance of each solution requiring a multi-criteria regret analysis. A linear criteria weighting approach (Duckstein and Opricovic, 1980) aggregates the three criteria into a cumulative value of regret:

$$L(s,j) = \sum_{c=1}^{n} w_c * D_c\,(s,j) \tag{4.4}$$

Where *L(s,j)* is the metric of cumulative regret, $D_c(s, j)$ is a standardised measure (see Equation (4.5) representing the deviation of performance criterion *c* from the ideal value for that criterion and *n* is the total number of performance criteria. Each criterion is weighted by w_c, ($0 \le w_c \le 1$) and $\sum_c w_c = 1$. Because the performance criteria used in this study do not have commensurable units, $R_c(s,j)$ cannot be used in Equation (4.4). A standardised measure of regret, $D_c(s,j)$, ensures the regret of each criterion falls within a [0,1] interval:

$$D_c(s,j) = \frac{|P_c(s',j) - P_c(s,j)|}{|P_c(s',j) - P_c(s^*,j)|} \tag{4.5}$$

where s^* = the worst performing strategy for the input set *j*.

Figure 4.2 shows box and whisker plots of normalised regret for the five performance criteria and the multi-criteria aggregate regret. Relative performance is assessed on three ordering statistics: the lower quartile (lower end of the box), median (red line inside the box) and the upper quartile (upper end of the box) value of regret for each IP. The candidate IP is selected based on the median regret.

Figure 4.2 f (Energy consumption regret), the easiest to interpret, shows all IPs including DESAL140 have median energy regret close to 1 and IPs with DESAL80 have near-zero regret. Desalination is twice as energy intensive as RST and eclipses the pumping energy requirements (Table 4.4).

IP 17, which includes the RST, has the lowest median regret (median regret is 0) because the RST perennially provides out-of-Thames-basin flow (unlike the UTR which frequently empties during severe droughts) and thus relies least on desalination.

Figures 4.2 b, c and e show regret for service reliability, storage vulnerability and environmental performance. IPs with more and larger infrastructure perform better with these criteria as they can supply more water during droughts. IP 1, the baseline IP, has the highest median regret followed by IP 2 which includes SLARS. SLARS has little effect on median regret of IPs in the service and environmental performance criteria. Increasing desalination output to 140 Ml/day strongly reduces median regret in all IPs as does the UTR. Larger UTR capacities improve regret. In all three criteria the increase in regret from running desalination at 80 Ml/day rather than 140 Ml/day outweighs the amelioration in median regret that the UTR100 provides over the UTR75. In all three criteria, IP 20, which includes the RST, DESAL140 and SLARS, has the lowest median regret.

IP19 performs nearly as well followed by IPs 16 and 15 which replace the RST with the UTR150. IPs with less and smaller infrastructure (e.g. IPs 1 and 2) perform better in the cost criterion (Figure 4.2 c). SLARS results in a small increase in cost regret as does the higher desalination output due to high energy use. The RST incurs large capital and operating costs leading to the highest regret values. IP 20, the most costly portfolio in every modelled future, has regret values approaching 1.

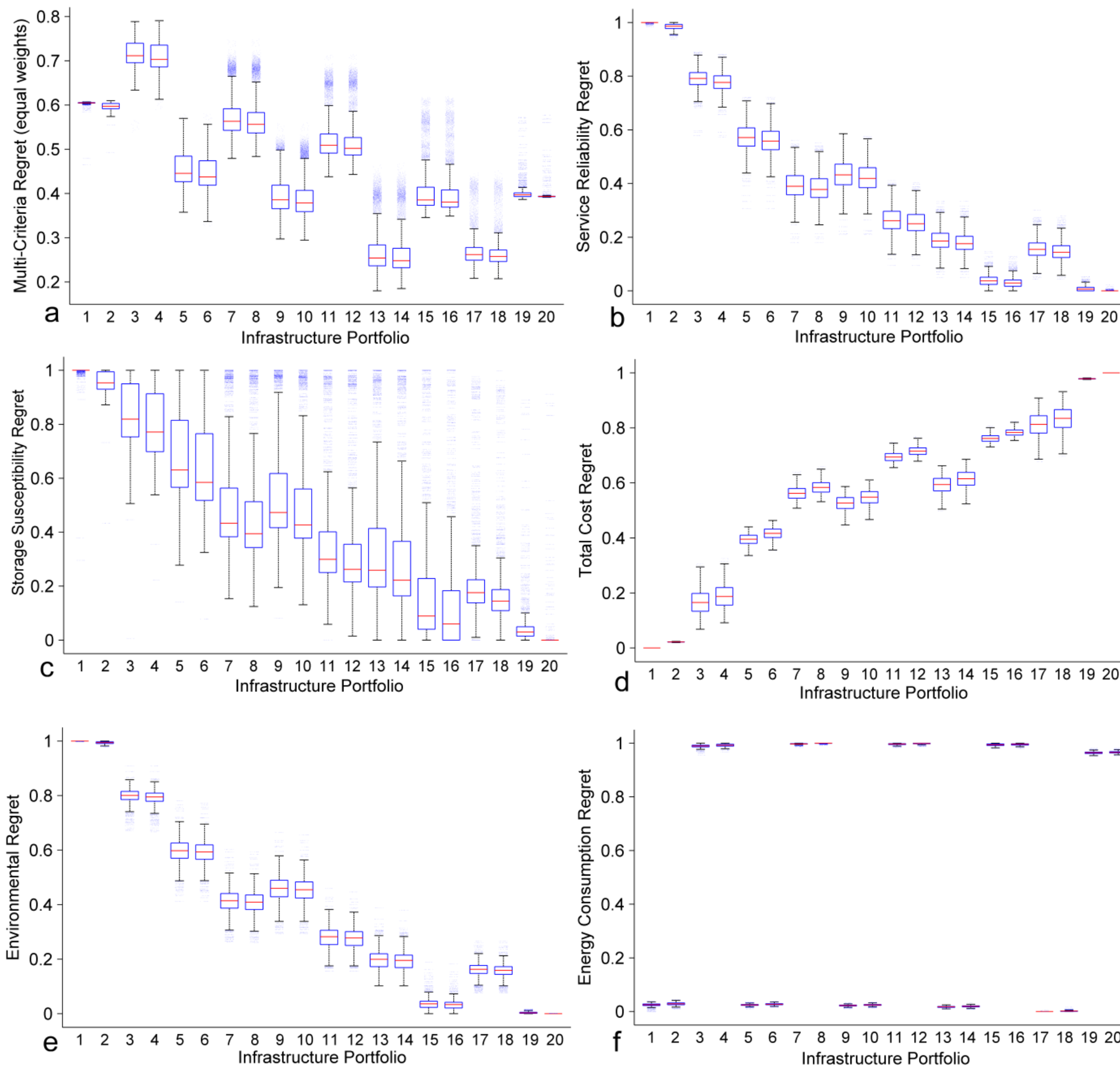


Figure 4.2 (a-f) Box and whisker plots of regret in each of the five performance criteria and an aggregated regret calculated using equal weighting of all criteria. The median fractional regret is represented by the red line in each box. The top and bottom of the boxes are the upper and lower quartiles respectively whilst the whiskers represent the regret value within 1.5 times the interquartile range from the upper and lower quartiles. Points represent outliers.

Figure 4.2 a shows equally weighted multi-criteria regret. All options with DESAL140 have higher regret than with DESAL80 and regret decreases with higher UTR volumes. IPs with RST and UTR 150 have similar regret values. IPs 13, 14, 17 and 18 have the lowest regret values. Table 4.6 summarises the lower quartile, median and upper quartile regret of the four best performing IPs.

In this case study the option with the lowest median value of regret, IP 14, is chosen to take forward to the next RDM phase.

Table 4.6. Upper quartile, median and lower quartiles of regret for IPs 13, 14, 17 and 18

	IP 13	**IP 14**	**IP 17**	**IP 18**
Upper quartile	0.284	0.276	0.278	0.272
Median	0.254	0.248	0.262	0.258
Lower Quartile	0.236	0.232	0.249	0.246

4.3.3.2 Characterising vulnerabilities of the candidate strategy

Having identified infrastructure portfolio 14 (UTR150, DESAL80, SLARS) as the candidate strategy, RDM's scenario discovery stage identifies under which combinations of uncertain parameters IP 14 is vulnerable to failure. Following Bryant and Lempert (2010) a modified version of the Patient Rule Induction Method (PRIM) (Friedman and Fisher, 1999) is used to characterise the vulnerabilities of IP 14. Vulnerabilities are defined as combinations of input conditions that produce higher levels of failures as compared to the failure level over all combinations considered.

PRIM is an interactive statistical cluster-finding algorithm that finds one or more low-dimensional boxes, or 'scenarios' in a hyper-dimensional space where the density of interesting points inside each box is higher than the space outside the box. PRIM seeks to maximise the density, coverage and interpretability of boxes. Density is defined as the total number of interesting points (in this case failure points) over the total points inside the box whilst coverage is the total number of interesting points inside the box compared to the total in the entire space. A trade-off or balance between coverage and density must be subjectively made by the analyst. Interpretability is how easily decision makers can interpret each box as a coherent 'scenario'. Interpretability is approximated by the number of dimensions that define each scenario.

A modified version of PRIM using the "Scenario Discovery Toolkit"[3] in the publically available statistical computing environment 'R' was applied which implements the PRIM code with a variety of useful features and visualisations (Bryant and Lempert, 2010). The Scenario Discovery Toolkit produces density vs. coverage trade-off plots. Each point on the plot represents a unique scenario described by one or more dimensions, and each dimension is represented by one uncertain system parameter. The analyst selects the box with an appropriate density to coverage ratio. Once a box or 'failure scenario' has been identified, the failure points inside the box are removed from the solution space and a new plot can be generated in order to find additional boxes. This process is repeated until the decision maker is satisfied by the boxes identified.

Each member of the solution space for IP 14 is classified as success or failure using only four of the five performance criteria: service supply reliability, storage vulnerability, environmental performance and total energy consumed. Total cost was not used because all IP 14 runs have the same capital and fixed operating costs and only variable operating costs differ and are directly proportional to the energy consumption. This resulted in a failure density of 54% with the majority of failed simulations resulting from failure in the service reliability criterion.

Two vulnerability scenarios were identified using PRIM covering 78% of all failure points with a density of 93% inside these two scenarios. In total the vulnerability scenarios include 44% of all simulations. Figure 4.3 a-b shows the density vs. coverage trade-off plots generated by PRIM (called 'peeling trajectories' in PRIM jargon). The colours of the points represent each dimension being constricted; a change in colour represents the construction of a new uncertainty dimension. The circled points represent the boxes chosen as having the appropriate coverage and density to describe scenarios. Choosing an alternative point in Figure 4.3 a would result in PRIM generating an alternate subsequent trade-off curve (Figure 4.3 b) as choosing an alternative scenario would result in different points remaining in the solution set.

[3] http://cran.r-project.org/web/packages/sdtoolkit/index.html

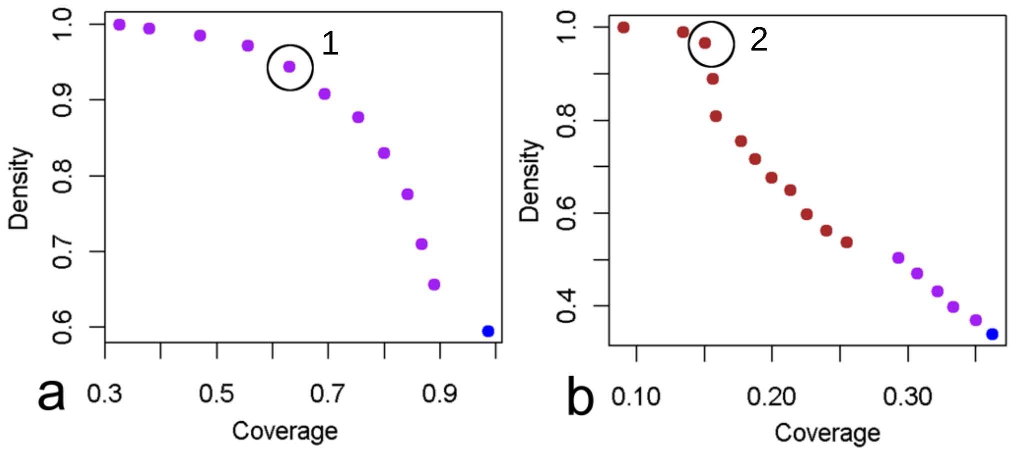


Figure 4.3 Density vs. coverage trade-off plots produced by the Scenario Discovery Toolkit. Colours represent different dimensions. Circled points were chosen as vulnerability scenarios 1 and 2.

The dimensions and boundaries of the chosen vulnerability scenarios are outlined in Table 4.7 whilst Table 4.8 provides the density and coverage of each box.

Table 4.7 Dimensions and boundaries of the two vulnerability scenarios identified using PRIM for infrastructure portfolio 14.

Scenario/Dimension	**1**	**2**
Fractional change in summer hydrology	<0.92	<0.94
Fractional change in winter hydrology	-	<0.87
London Demand (Ml/day)	>2098	>1933

Table 4.8 Density and coverage of the two vulnerability scenarios for infrastructure portfolio 14

Scenario	**Density**	**Coverage**
1	0.94	0.63
2	0.97	0.15
Total	0.95	0.78

Scenario 1 describes futures where summer river flows are more than 8% lower than historical (1920-2005) and London's mean annual demand is greater than a 2098 Ml/day. In this scenario these dry summers cause IP 14 to fail, even with moderate water demand (~2100 Ml/day). The high coverage (63%) of this scenario shows IP 14 is vulnerable to dry summers (8% lower flows than the historical average) combined with moderate to high demand levels (>2098 Ml/day).

Change in winter hydrology is not included in this scenario because changes in winter hydrology do not substantially affect this IP. In futures where summer flows are low (>8% lower than the historical average), the system suffers from a lack of storage and cannot buffer the summer-winter disparity in flow, even with the desalination plant providing 80 Ml/day of additional supply during droughts.

Scenario 2 describes a scenario where London's mean annual demand ranges from low (in the interval between the first and second deciles) to high and includes dry summers and winters (6% and 13% drier than historical respectively). This failure scenario shows that IP 14 performs poorly under these year-round dry climates no matter how low demand is.

The density of both scenarios is high (94% and 97% for scenario 1 and scenario 2 respectively) suggesting that these scenarios are exceptionally dangerous for IP 14.

4.3.3.3 Initial findings and recalculating regret

Overall, moderate to high London demands combined with moderately dry summers cause IP 14 to fail. Low future demands when confronted with dry summers and winters (6% and 13% drier than historical respectively) also lead to frequent system failure.

To check if any other IPs perform better under these vulnerability scenarios, regret is recalculated for all IPs for futures that fall within the range of conditions dictated by vulnerability scenarios 1 and 2. The regret for all futures outside of the two scenarios was also examined. Regret plots for both scenarios are provided in the supplementary material. IP 18 has the lowest median regret inside the scenarios whilst IP 14 has the lowest median regret outside each scenario. Therefore, there is a trade-off between IP 14 and IP 18. Because of the similarity between the scenarios and this single trade-off, scenarios 1 and 2 were combined into a single vulnerability scenario and multi-criteria regret was recalculated for all futures inside and outside of the conditions defined by vulnerability scenarios 1 and 2 (Figure 4.5 a and b).

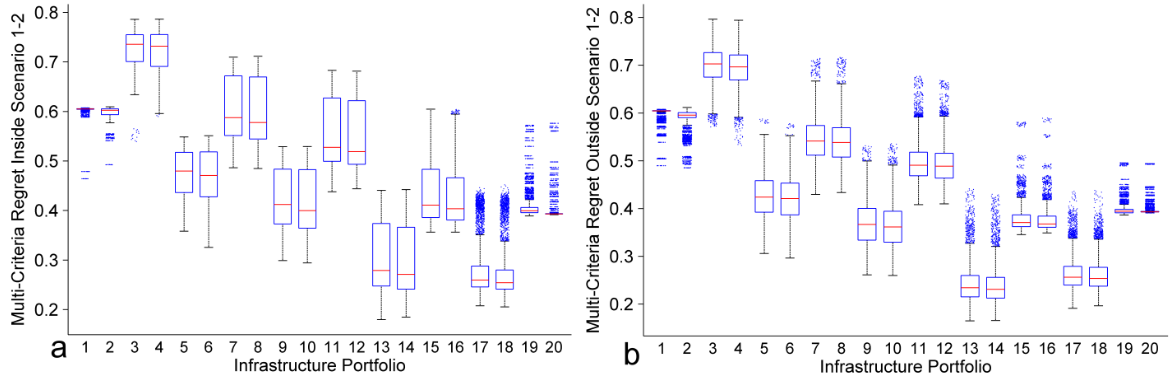


Figure 4.4 a) Multi-criteria regret of all modelled futures in both vulnerability scenarios and b) regret of all modelled futures outside the two vulnerability scenarios

IPs 13, 14, 17 and 18 are still the best performing IPs for futures contained within the two vulnerability scenarios. Table 8 and Table 9 summarise the lower quartile, median and upper quartile regret values of the four best performing IPs. For futures inside the two scenarios, regret is higher for all four IPs. However, the increase in the range of regret for values not considered outliers is considerably greater for IP 13 and 14. IP 18 has the lowest upper quartile and median value of regret in scenarios 1-2. Compared to the increase in range of regret for IP 14, the range in regret increases minimally (median regret remains the same) indicating that IP 18's relative performance remains stable inside and outside the vulnerability scenarios. For futures outside the vulnerability scenarios, IP 14 has the lowest regret values for each of the ordering statistics.

Table 4.9 Upper quartile, median and lower quartiles of regret for IPs 13, 14 and 17 for futures comprised in vulnerability scenarios 1-2.

	IP 13	**IP 14**	**IP 17**	**IP 18**
Upper quartile	0.374	0.366	0.288	0.280
Median	0.279	0.271	0.260	0.254
Lower Quartile	0.248	0.241	0.246	0.241

Table 4.10 Upper quartile, median and lower quartiles of regret for IPs 13, 14, and 17 for futures outside vulnerability scenarios 1-2.

	IP 13	**IP 14**	**IP 17**	**IP 18**
Upper quartile	0.260	0.256	0.279	0.277
Median	0.234	0.231	0.256	0.254
Lower Quartile	0.215	0.213	0.240	0.238

Figure 4.5 shows the median regret of each of the twenty IPs. IP 18 has the lowest median regret inside scenarios 1-2 whilst IP 14 has the lowest median regret in all futures outside the scenarios. Relative to the regret of every other IP however, the difference in median regret between the IP 14 and 18 is small.

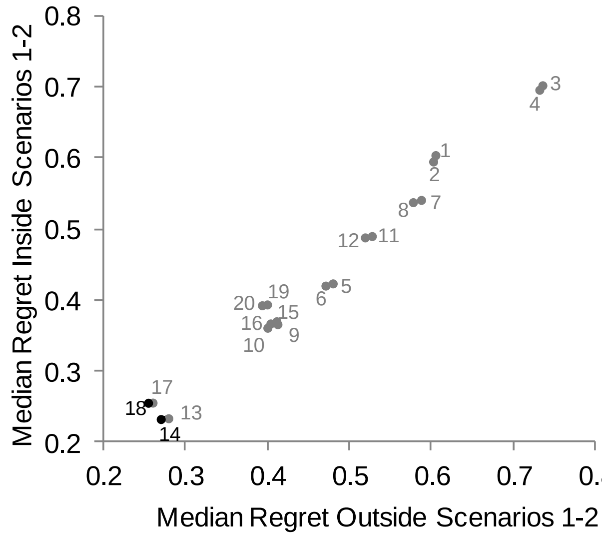


Figure 4.5 Median multi criteria regret of each of the twenty policies inside and outside scenarios 1 -2 IP 18 has the lowest median regret inside the vulnerability scenarios whilst IP 14 has the lowest regret outside the scenarios.

IP 14 and IP 18 are the same except IP 14 includes the UTR150 and IP 18 includes the RST. Both the UTR150 and the RST provide the same amount of water to the Thames at the beginning of droughts. The UTR however has maximum storage and is refilled from the Thames which cannot occur during droughts whilst the RST in this model continuously provides water from a neighbouring wetter region.

The RST is costlier and more energy intensive, but has better performance in the storage, service and environmental performance criteria. IP 14 however is vulnerable because it lacks the storage necessary to maintain service during extended droughts. RDM suggests that these two strategies are likely to be the most robust into the future.

4.3.4 Discussion on the supply-side portfolio RDM application

An RDM analysis begins by the selection of a candidate strategy. In this case study, the RDM process began with a multi-criteria regret analysis. A full grid solution space of 311,080 simulations was generated using a computationally efficient system simulator. The solution space included dire, mild and opportune plausible futures allowing the comparison of IPs under a wide range of conditions. Each IP was compared to the best performing IP for a given set of input parameters. The median relative regret was used to select IP 14 as the candidate strategy. The initial regret analysis also provided information on the relative performance of each IP e.g. SLARS has minimal effect on the levels of regret and IPs with DESAL140 have higher regret in the cost and energy criteria than DESAL80.

The second step of the RDM framework involved a scenario discovery process using PRIM to isolate scenarios in which the candidate strategy is likely to fail. Two scenarios were identified: one which includes futures with dry summers and moderate-to-high demand and a second with dry summers and winters and low demand. In total 78% of failure points were covered in the two scenarios albeit with a high density (95%). Given the spread of failure points around the solution space, PRIM was unable to produce scenarios with a better coverage to density ratio. This is a result of having multiple performance criteria that conflict; i.e. better environmental, storage and reliability performance often results in high energy consumption and high costs generating failures that are spread throughout the solution space.

From vulnerability scenario 1 (which includes dry summers) and the regret analysis on vulnerability scenarios 1 and 2, IP 14 was identified as vulnerable to failure because of its inadequate storage under droughts making it unable to compensate for the summer/winter hydrology disparity in climates that have dry summers. The RST was identified to be a useful, but an expensive and energy intensive alternative to address this disparity. The Severn basin was assumed to not experience drought at the same time as the Thames basin. A spatial drought correlation study would be required to establish the reliability of the RST and consider it in this study. This implies that the ‘IP 14 or 18’ decision cannot be made by planners and that the relative strength of plans including the RST could be further lowered in regards to reliability. The price of energy was not found to affect the vulnerability of IP 14 because the majority of system failures come from the service reliability criteria.

In a full RDM analysis, decision makers could improve IP 14 and possibly IP 18 devising new IPs which could be resubmitted into the RDM process. The process would be repeated until a suitably robust IP is identified.

Several limitations affect the relevance of the results for real Thames region planning. The England and Wales water sector follows a 'twin-track' approach including both supply augmentation and demand management (e.g. water conservation, increased efficiency, metering, leakage reduction, communication campaigns, etc.). This study only considers supply augmentation schemes to balance supply and demand; the next section will bring in demand management options. Uncertainty about the reliability of the River Severn Transfer should be considered, but without a water resource model of that area it was not possible to consider it in this study. This would add a further dimension of uncertainty and significantly increase the computational burden of the planning problem. Further work could include this source of uncertainty and use sparser sampling methods for RDM. In this application a normal distribution was assumed for future demands but distributions were not available for the climate change hydrologies and energy costs (a uniform distribution was used). As these probabilities were unknown, probabilities for the vulnerability scenarios were not assigned. These improvements would increase the planning relevance of study results but would likely not significantly change methodological implications, the focus of this chapter.

4.4 RDM application including infrastructure expansion and demand management options in the Thames basin

The initial RDM application included only supply options. However, demand management (DM) options are also likely to be part of a future robust strategy in the Thames basin (Thames Water, 2010). The second application of RDM in this chapter includes both supply and demand options. Adding DM options results in the planning problem becoming significantly more computationally expensive.

4.4.1 Demand Management Options

Demand management options are considered for demand nodes representing water use by Thames Water, Essex and Suffolk Water and Veolia Three Valleys Water. In the water company Water Resource Management Plans (Essex and Suffolk Water, 2010; Thames Water, 2010; Veolia Water Central Limited, 2010) DM schemes are divided into three categories: metering, leakage reduction and water efficiency measures.

Leakage reduction options include: mains renewal or replacement, pressure management, increase of speed of repair, new detection technologies, district metering, and global supply pipes.

Pro-actively fixing leaks before they're reported is referred to as active leakage control (ALC). For ALC planning water companies consider 'tranches' (bundles) of ALC implementation; each tranche is a different option with prerequisites (option 'active leakage 2' can only be activated after 'active leakage 1', etc.). Successive leakage control activities result in diminishing returns: the water savings resulting from each successive tranche increase capital and operating costs increase substantially.

Metering options include targeted compulsory metering and change of occupancy metering. Metering savings are estimated based on the number of meter installations water companies propose to implement in their five-year business plans. Although metering savings are expected to rise as properties are metered then remain constant, since only the year 2035 is modelled the study uses a constant saving profile.

Water efficiency options include household and commercial customers audit programmes and water efficiency awareness campaigns. Savings can rise over their implementation program (typically 5 years long) and typically decrease afterwards according to observations by water companies. As this RDM application is concerned with the year 2035, a static savings profile is considered. Water efficiency options also include the possibility of imposing different tariffs strategies. 'Rising Block Tariffs' and 'Summer Winter Tariffs' are included as options. Metering is prerequisite to tariffs options.

4.4.2 Proposed portfolios of supply and demand management schemes

The RDM application examines the robustness of different portfolios of supply and demand management options proposed in company WRMPs. The study is focused on the London WRZ so supply options are limited to those proposed by Thames Water. The same options are considered in this case-study as the supply-only study in Section 4.3 except in this study the desalination plant operates at a single capacity, 140 Ml/day.

Of the possible demand management options described in Section 4.4.1 those considered include active leakage control (ALC), mains replacement (MAINS), water efficiency improvements (EFI), compulsory metering (MET) and seasonal tariffs (contingent upon the implementation of household metering). To reduce the number of DM options, pressure management was included in active leakage control and customer supply pipe leakage reduction was aggregated with mains replacement.

Thames Water (2010) predicts that compulsory metering will provide the same demand savings as change of occupancy metering with lower capital costs so only targeted compulsory metering is considered. In the RDM application DM scheme implementations have fixed capacities that are scaled according to the demand levels modelled to keep the number of simulated strategies manageable. DM options are activated to the fullest extent described in the water companies' WRMPs; partial implementation of DM options is not considered in this RDM study. It was assumed all DM and supply options can be fully implemented in 2035.

The selection of supply options incurs the same capital and fixed and variable operating costs described in Table 4.4. As in Section 4.3 fixed and variable operating costs are also incurred by existing supply infrastructure. Variable operating costs for supply options consider energy costs of pumping and desalination. Consumption is multiplied by the energy price resulting in variable cost. DM schemes do not require energy use but may require other variable operating costs. Capacities of supply options and demand reduction of DM options (except for seasonal tariffs) are obtained from WRMPs.

In 2009 VTVW began implementing a trial seasonal summer/winter tariff for a small number of its metered customers. The seasonal tariffs calculated for each water company in this study are based on this trail tariff. The effect of seasonal tariffs on demand was estimated using price elasticity of demand and the point expansion method to estimate the demand function at a known point on the demand curve (Griffin, 2006; Veolia Water Central Limited, 2011). Price elasticity is defined as the percentage change in demand that will occur for a percentage change in water price. Assuming a constant price elasticity, ε, of -0.15 (Herrington, 2007) and that the demand curve can be approximated as linear the demand function becomes

$$w = \left(\frac{w_n}{p_n} * \varepsilon\right) p + b \tag{4.6}$$

where *w* is the water demand, (p_n, w_n) is a known point on the demand curve, *p* is the price of water and *b* is a constant. Using this demand function the summer and winter demands that correspond to the winter and summer water prices for 2035 are estimated. This calculation is performed for each water company assuming they implement seasonal tariffs analogous to VTVW. Each water demand level considered for 2035 (detailed below) and the standard price of water per water company are used as the known points on the demand curve. Metering penetration estimates for 2035 were taken into account by only applying seasonal demands to the fraction of properties expected to be metered.

4.4.3 Uncertainties considered in the supply and demand option RDM application

The same four sources of future uncertainty are considered in the RDM study: hydrological variability, climate change perturbation of hydrological flows, water demand, and energy costs. The hydrological variability uncertainty and energy uncertainty is modelled exactly as it was in the supply only application (Section 4.3.2.1) using an 85-year hydrological time series and 14 energy costs obtained from the same equiprobable cost distribution respectively. Climate uncertainty was also similarly considered but instead of 101 climate scenarios only 25 were used in order to reduce the computational requirements.

Unlike in the supply-only RDM application which only considered uncertainty in London demand, this application considered demand uncertainty on the London, VTVW_Abs and VTVW+ESW_BS demand nodes using demand profiles represented by normal distributions. In the case of VTVW+ESW_BS, only uncertainty in the bulk transfer to the Essex WRZ component was considered as the VTVW transfer component of this demand node was considered negligible. The VTVW_T_BS demand was also considered to have a negligible effect on the system. The SWOX demand represents a reservoir operation rule and therefore demand uncertainty on this node is not considered.

A demand uncertainty profile for the London WRZ for 2035 was obtained from Thames Water (2010) and fitted with a normal distribution (μ = 2377 Ml/day, σ = 93.4). A normal distribution is used here instead of the gamma distribution used in the previous RDM study because this study is compared to a similar study using the Economics of Balancing Supply and Demand (EBSD) framework (Section 4.5) which uses the mean demand of this normal distribution. The expected VTVW_Abs demand was calculated using the expected 'distribution input' for VTVW's Central and Southern WRZs for 2035 from Veolia Water Central Limited (2006). Raw water and process losses in the Essex WRZ are considered negligible and it is assumed that TWUL would always contribute 22.5% of the WRZ's demand to calculate the demand of the VTVW+ESW_BS. To represent uncertainty in the VTVW_Abs and VTVW+ESW_BS demands σ is proportionally adjusted assuming the distribution from TW is applicable.

Nine levels of demand were considered using deciles of the three normal demand uncertainty profiles. Including the 0.01 and 0.99 percentiles raised the total demand values considered to 11. Demands are considered perfectly correlated between the demand nodes, all demands increase or decrease by the same proportional amount. Correlation between demand nodes was assumed to limit the number of possible futures and keep the analysis computationally manageable.

4.4.4 Performance criteria used in the supply and demand option RDM application

Several performance metrics are used to investigate each strategy: environmental performance, energy consumption, total costs (capital and operating) and a composite measure of engineering robustness. The environmental performance (Shortage Index at Teddington), energy consumption (total energy use) and total cost metrics (operating and capital) are identical to and have the same limitations as those used in the supply only RDM application (Section 4.3.2.2).

In the supply and demand option RDM application three engineering performance measures are considered including service reliability, storage resilience and susceptibility. In the regret analysis described below, normalised versions of these metrics are combined into one aggregate criterion named ‘engineering robustness’ using equal weighting using Equations (4.3)-(4.5). Aggregation results in a loss of information and choosing different weightings of the varying criteria would affect the aggregate values. Equal weightings were assumed in this analysis but in a situation where multiple stakeholders are present different weightings could be used dependent on stakeholder preferences and the regret of each criteria could be discussed without aggregation as in Section 4.3.

The service reliability metric summarises how often water use restrictions come into effect during a simulation (as defined by the LTCD) and is calculated analogous to the one used in the supply only application (Equation (4.1) except that in this application it represents annual rather than weekly reliability:

$$\mathrm{R_i} = \left(1 - \frac{\mathrm{Y_{fail,i}}}{\mathrm{Y_{sim}}}\right) \tag{4.7}$$

where Y_{fail} is the number of years during which restriction level *i* was imposed at least once and Y_{sim} is the total years in the simulation. Reliability for water use restriction levels 2 (L2) and 3 (L3) restrictions are considered in this study which correspond to a sprinkler and hosepipe/non-essential use bans respectively. Annual reliability is used here instead of weekly reliability because this study is later compared to a similar study using the EBSD framework (Section 4.5) which uses annual reliability.

The resilience metric is defined as the average duration (in weeks) of L2 and L3 failures and corresponds to the resilience described in Hashimoto et al. (1982).

The storage susceptibility metric is identical to the one described in Section 4.3.2.2 and is the lowest storage level reached by LAS in a simulation.

4.4.5 Supply and demand option RDM application

The robustness of 240 unique combinations ('portfolios') of supply and demand management options was investigated considering uncertainty in demand, hydrology and energy costs. A full enumeration of uncertainty distributions including 25 climate scenarios, 11 levels of demands (London, VTVW_Abs, and VTVW+ESW_BS), and 14 energy costs for each of the 240 portfolios created a solution space of 924,000 simulations; each portfolio is tested under 3850 plausible futures.

4.4.5.1 Candidate strategy selection

In the first step of RDM, candidate strategy selection is performed as it was for the supply-only RDN application. The candidate strategy is one of the 240 unique portfolios. As in Section 4.3.3.1, multi-criteria regret based analysis (Equation (4.3) was used to select the overall best performing strategy in the four performance criteria.

Figure 4.6 shows a box and whisker plot of normalised aggregate regret. The four performance criteria are given equal weighting and are standardised to give values between 0 and 1. The median (targets inside the boxes), upper and lower quartiles (top and bottom of the boxes respectively) values of regret summarise the relative performance of each investigated portfolio. Figure 4.7 shows the regret of the first 49 portfolios. Portfolio 1 is the baseline strategy where no potential options are enabled. Each marked portfolio represents the activation of only one supply or demand option (beyond the existing system) showing how each option affects system regret. Baseline multi-criteria regret, the one that considers all performance criteria with equal weighting, is 0.64. Generally strategies with larger UTR volumes (with the RST considered to be a type of UTR) have lower regret (e.g. 0.59 for UTR75, 0.56 for UTR100, 0.51 for UTR150 and 0.42 for RST). The installation of meters (0.54) seasonal tariffs (0.45), and replacing mains (0.50) all reduce regret. The activation of SLARS slightly increases regret (0.66) whilst enabling active leakage control strongly increases regret (0.76) because of this option's high operating costs.

Portfolio 210 (RST, no SLARS, and all DM options activated except for active leakage control) has the lowest median regret (0.18) and is chosen as the candidate strategy to continue the RDM process.

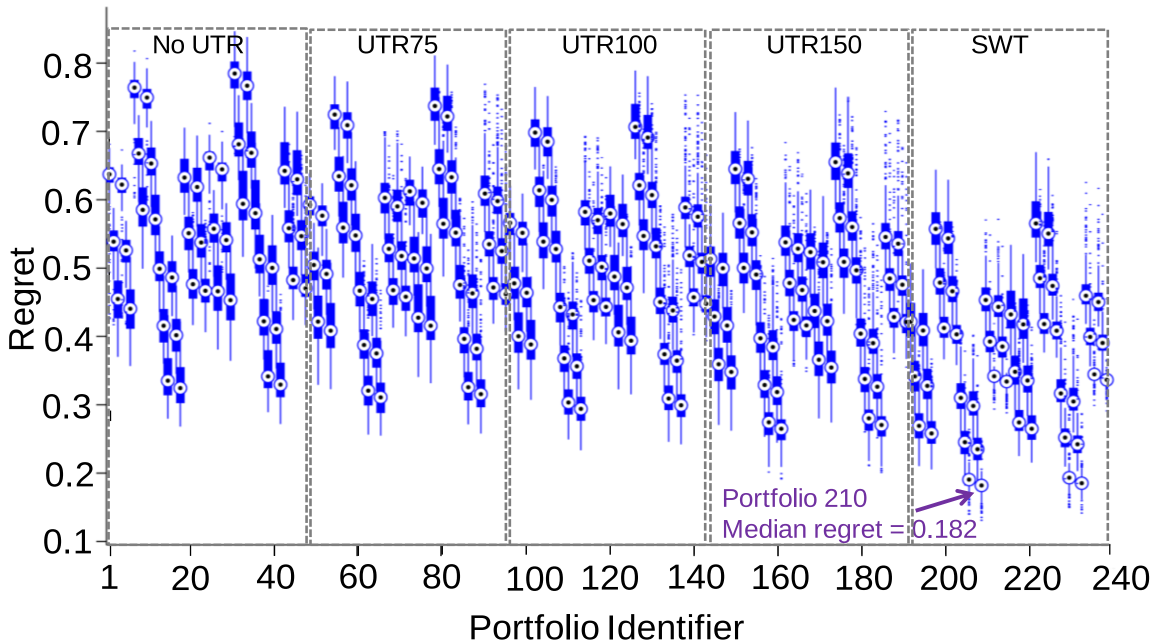


Figure 4.6 Box and whisker plot of multi-criteria regret of the four performance criteria given equal weighting. The targets inside the boxes represent the median regret for each portfolio. Regret of similar strategies reduces with higher UTR volumes (RST is considered to be a type of UTR). Portfolio 210 has the lowest median regret.

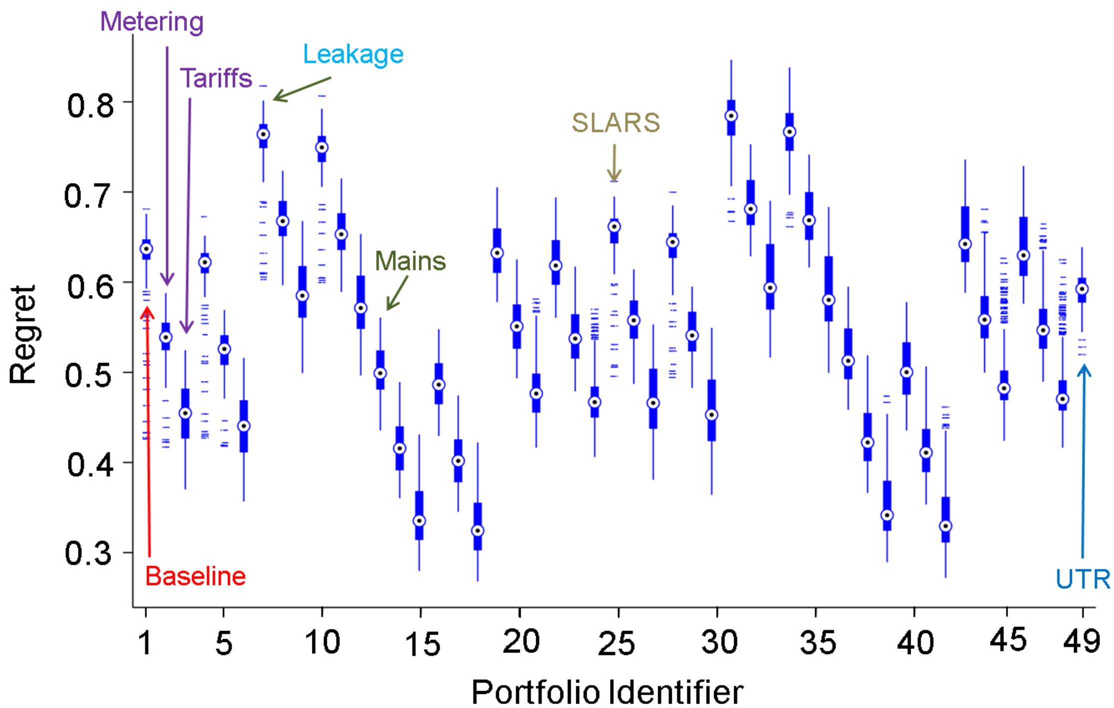


Figure 4.7 Effect of individual supply and demand options on regret in relation to the regret of the baseline strategy. Metering, sophisticated tariffs (Tariffs), mains replacement (Mains) and SLARS reduce regret. Active leakage control (Leakage) and SLARS increase regret. Unlabelled portfolios are combinations of the labelled options.

4.4.5.2 Vulnerability characterisation

The subsequent RDM step is to characterise candidate strategy vulnerabilities under the 3850 plausible futures (25 climate scenarios x 11 levels of demands x 14 energy costs). Using engineering robustness, environmental performance and total variable operating costs performance criteria each simulation is classified as a success or failure. The total energy criterion was not included because energy consumption is reflected in variable operating cost. Capital costs are not included because all simulations for strategy 210 have the same capital costs.

Except for the service reliability and reservoir vulnerability components of the engineering robustness criterion, for lack of a more precise cut-off, the worst 15% of simulations in each criterion were classified as failures. The 15% percent failure threshold was selected as it resulted in a similar amount of failures in each criterion as compared to the other metrics to avoid a bias in system failure to a single criterion. According to Thames Water (2010), sprinkler (L2) and hosepipe/non-essential use bans (L3) should not occur more often than once every 10 to 20 years respectively corresponding to 0.9 and 0.95 annual reliability in Equation (4.7). Because of pressure-related distribution problems in the supply network the storage susceptibility threshold for LAS was set to 22.5% of its capacity (45 Mm^3) (Cookson and Weston, 2008). Failure in at least one criterion designates the whole simulation a failure. Applying these thresholds results in 28% of runs being designated failures.

Following Bryant and Lempert (2010), a modified version of the Patient Rule Induction Method (PRIM) (Friedman and Fisher, 1999) was used to determine under which combinations of input conditions the candidate strategy is likely to fail. PRIM is an interactive statistical cluster-finding algorithm that finds one or more low-dimensional boxes in a hyper-dimensional space where the density of relevant points inside each box is higher than in the space outside the box. Density is defined as the total number of interesting points (in this case failure points) over the total points inside the box whilst coverage is the total number of failure points inside the box compared to the total in the entire space. More details on how PRIM was used can be found in Section 2.2.

Four vulnerability scenarios were identified covering 83% of failure simulations with an overall failure density of 90%. Table 4.11 summarises the density and coverage of the four vulnerability scenarios and provides their dimensions.

Vulnerability scenario 1 describes a scenario where demand values fall in the last (higher) seven deciles of modelled demand and river flows are significantly drier than the historical average. This scenario shows that Portfolio 210 is not able to cope if both summers and winters become significantly drier than before even if demand is low. Dry winters prevent surface and underground storage from storing enough water to supply demand during the dry summers even though demand management measures including summer tariffs help to reduce demand. With 46% coverage this is the biggest vulnerability scenario.

Dry summers and moderately dry winters combined with moderately high energy costs describe scenario 2. In this scenario, enough water is stored during winter to supply demands with the help of energy intensive options (desalination plant and RST) however the energy intensity of these supply options cause ‘failures’ due to high operating costs.

The third scenario includes high demand levels (10th and 11th deciles), modestly dry summers and winters that are up to 20% wetter than the historical average. There is not enough surface storage to buffer winter/summer flow disparity at such high demand levels despite the relatively wet winters and lower summer demands as a result of seasonal tariffs.

The final vulnerability scenario includes the same seasonal flow changes as the third scenario, almost the full spectrum of modelled demands and disproportionally high energy costs.

Table 4.11 Characterising the four dimensions of the four vulnerability scenarios and their density and coverage.

Scenario/ dimensions and properties	**1**	**2**	**3**	**4**
Fractional change in summer hydrology	<0.81	<0.86	<0.91	<0.91
Fractional change in winter hydrology	<0.84	<0.91	<1.21	<1.21
Demand decile (Ml/day)	>3rd	-	>10th	>1st
Energy cost (£/kWh)	-	>0.175	-	>0.215
Density	0.90	0.83	1.00	1.00
Coverage	0.46	0.22	0.10	0.04

Figure 4.8 shows the distribution of volumetric contributions from demand management options for portfolio 210 over the 3850 simulations. Demand management options continuously reduce demand whilst supply options are only activated during droughts therefore on average demand management options contribute more to the supply-demand balance in the RDM recommended plan.

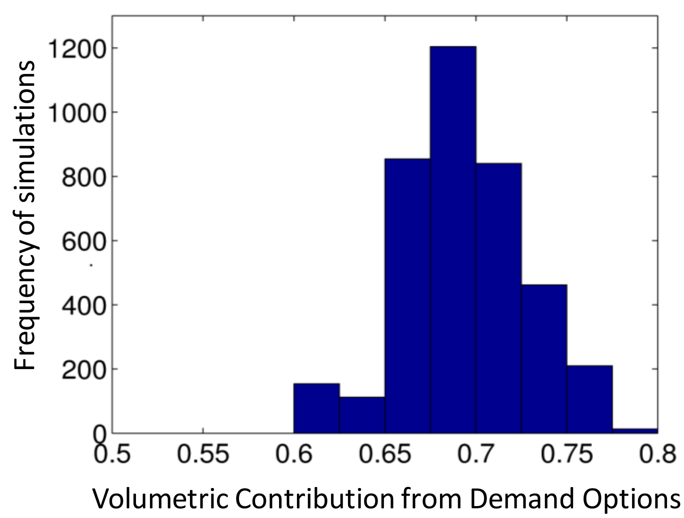


Figure 4.8 Cumulative (over 85 years) volumetric contribution of all demand management options to the regional supply-demand balance for portfolio 210 as a fraction of total contribution of supply and DM options. Overall DM options contribute more than supply options in recommended portfolio 210 (on average 69%) because they reduce overall demand continuously whilst the set of chosen optional supply options (in this case only RST) are only activated during droughts. In dry climate scenarios the contribution of DM options is greater as they do not require surface water inflow to reduce demand as opposed to supply options which rely on stored surface water.

4.4.5.3 Next steps

This study performs only one pass of the RDM iterative framework. In a full RDM application managers and analysts would sift through the failure scenarios and target vulnerabilities they found most significant or probable by proposing incremental improvements to the candidate strategy. Active water company participation was not available during this study so only one pass was completed. Decision makers may use the probabilistic information contained in the probability distributions used to generate plausible future conditions to judge whether they should take steps to hedge against these vulnerabilities. Modified system designs could be tested using more detailed simulation models under the identified vulnerability scenarios. Once a new design is proposed, the scenario discovery step could be repeated until a satisfactorily robust strategy is achieved.

4.4.6 Discussion on the supply and demand RDM application

First the portfolios of supply and demand management schemes recommended by RDM are compared. From the supply options, RDM suggested RST and not SLARS due to its cost outweighing the service and environmental improvements. However, the regret of the identical portfolio including SLARS had a regret of 0.185 compared to 0.182, a 1.6% increase in regret. The proposed Upper Thames Reservoir (UTR) is not selected. This is partially explained by the fact that in this study RST did not have a capacity limit and was therefore able transfer water to the Thames when the UTR would have emptied. The RDM portfolio with UTR replacing RST scored a multi-criteria regret of 0.265, the 11th best performing portfolio.

Demand management options chosen by RDM in this study include enhanced water efficiency, compulsory metering, seasonal tariffs and the replacement of distribution mains for the Central, Southern, Essex and the London WRZs. To reduce the number of portfolios considered and reduce computation time in the RDM study DM options were applied to their fullest extent in every WRZ. This discourages DM options that are not cost-effective to implement in some WRZs but are in others and discourages options with diminishing returns to scale such as ALC which was not selected in the RDM application.

Some DM options such as water efficiency do not follow a constant savings profile. This RDM study did take into account dynamic savings profiles as it considered only conditions in year 2035. This can lead to the savings provided by DM options being over optimistic. Because of lack of data on time-varying water savings profiles for DM options in the optimisation approach, these were not included in this study and did not affect results.

In this application a normal distribution was assumed for future demands but distributions were not available for the climate change hydrologies and energy costs (a uniform distribution was used). As these probabilities were unknown, probabilities for the vulnerability scenarios were not assigned.

4.5 RDM as compared to EBSD

This chapter describes two applications of the RDM framework. One considered supply only infrastructure additions whilst the second included demand management options. The RDM framework was used to suggest robust candidate strategies (portfolios) that performed satisfactorily over a wide range of future scenarios including future climate change, demands and energy costs. The *scenario discovery* step, a hallmark or RDM, uncovered and quantified the vulnerabilities of the candidate strategies.

A similar supply and demand management problem was solved with the Economics of Balancing Supply and Demand (EBSD) planning framework (Section 1.5.2). EBSD uses an aggregated economic optimisation model to find the most optimal portfolio. This study is detailed in the Appendix. Below the results of the EBSD and RDM studies are compared and the benefits and limitations of each are discussed followed by recommendations on their joint use.

4.5.1.1 Comparison of the RDM and EBSD proposed scheme portfolios

Before comparing results of both approaches it is useful to consider the design of this study implies they are unlikely to be the same. Below differences in results between the two frameworks (inevitable in this case) are summerised and the broader differences of the approaches and their implications as revealed by the results are discussed.

The portfolios of supply and demand management schemes recommended by both planning frameworks (Table 4.12) are briefly compared. From the supply options common to both studies EBSD optimisation chose both SLARS and the UTR whilst RDM suggested SRT and not SLARS due to its cost outweighing the service and environmental improvements. However, the regret of the identical portfolio including SLARS had a regret of 0.185 compared to 0.182 in the RDM study, a 1.6% increase in regret. The proposed UTR is not selected in the RDM case. This is partially explained by the fact that in this study the SRT did not have a capacity limit and was therefore able transfer water to the Thames when the UTR would have emptied. The RDM portfolio with UTR replacing RST scored a multi-criteria regret of 0.265, the 11^{th} best performing portfolio. The EBSD model selects a total of 28 supply-side options and 37 DM options. The split of supply vs. DM options is roughly 50% in terms of volume supplied with DM options being adopted in early years followed by new supplies starting later. In the RDM recommended plan DM options contribute on average 69% of new contributions to the supply-demand balance. Figure 4.9 shows the options considered and selected by both frameworks. Table 4.12 provides explanations for the differences in options selected by EBSD and RDM.

Demand management options chosen by RDM in this study include enhanced water efficiency, compulsory metering, seasonal tariffs and the replacement of distribution mains for the Central, Southern, Essex and the London WRZs. The optimisation model chose a unique portfolio of demand management options for each WRZ. Metering options provide 35% of the total DM volume, water efficiency options 7% and active leakage control 58%.

To reduce the number of portfolios considered and reduce computation time in the RDM study DM options were applied to their fullest extent in every WRZ. This discourages DM options that are not cost-effective to implement in some WRZs but are in others and discourages options with diminishing returns to scale such as ALC which was not selected in the RDM application. In contrast the optimisation approach allowed considering WRZ specific DM investments at several levels which is why this approach recommends a larger DM contribution to the supply-demand balance.

Some DM options such as water efficiency do not follow a constant savings profile. This RDM study did not take into account dynamic savings profiles as it considered only conditions in year 2035 while EBSD considered dynamic passage through time. This can lead to the savings provided by the RDM DM options being over optimistic. Because of lack of data on time-varying water savings profiles for DM options in the optimisation approach, these were not included in this study and did not affect results.

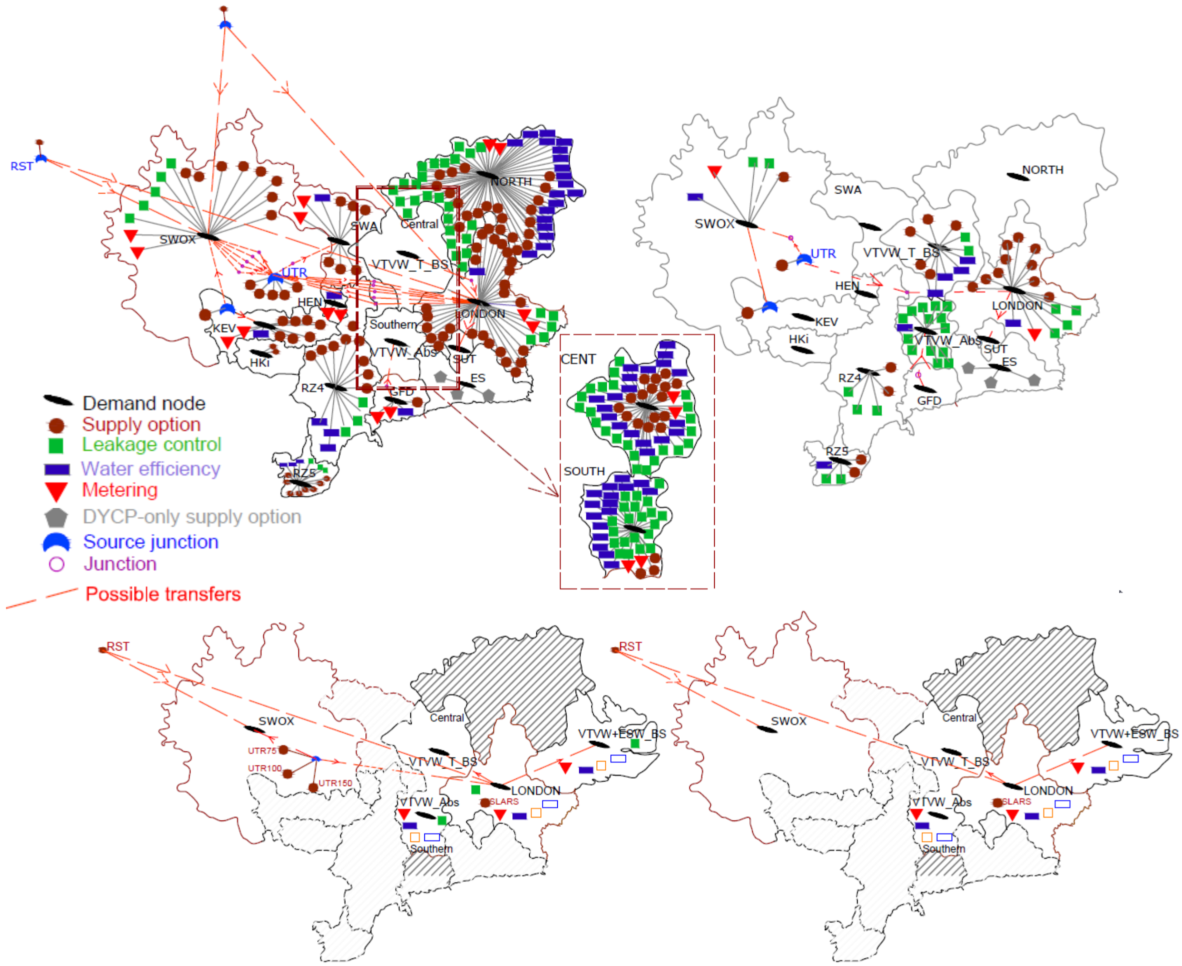


Figure 4.10 Plan view of the EBSD optimisation (top panels) and RDM (bottom 2 panels) results.Left panels show options considered by the modelling methods, right panels show what portfolios of supply and demand management schemes were favoured by each planning framework. Both approaches suggest a mix of new supplies and demand management schemes. Because these studies used draft WRMP data and focused on modelling methods rather than on exhaustive data collection and verification, these results should be considered only indicative suggestions for Thames region investment rather than a final assessment.

The two approaches are compared in terms of which options they pick. Comparing the performance of the EBSD and RDM chosen supply and demand management portfolios using the five performance metrics used in the RDM analysis is not possible without building a full simulation model of the EBSD solution (the EBSD network includes more WRZs not included in the RDM simulation model) and running it under the same possible future scenarios used in the RDM analysis. The EBSD method uses a constrained mixed-integer optimisation model that does not record the performance of the system in multiple criteria.

Table 4.12 Summary of supply and demand management options recommended by the capacity expansion optimisation and RDM approaches.

Option	RDM	EBSD
South London Aquifer Recharge Schemes (SLARS)	No	Yes
Upper Thames Reservoir (UTR)	No	Yes
Severn River Transfer (SRT)	Yes	No
Mains replacement (MAINS)	Yes (all WRZs)	In the LDN WRZ
Active leakage control (ALC)	No	Three l levels in LDN level 1 and 2 in SWOX 14 levels in SOUTH ALC options in CENT, RZ4and RZ5
Metering (MET)	Compulsory metering (all WRZs)	Targeted compulsory metering in the LDN WRZ and change of occupancy metering in SWOX
Seasonal Tariffs (SETA)	Yes (all WRZs)	No
Water efficiency (EFI)	Yes (all WRZs)	LDN, SWOX, SOUTH, CENT and RZ5 WRZs

4.5.1.2 Benefits and limitations of the EBSD least-cost optimisation approach

EBSD uses annual aggregate estimates of supply, demand and uncertainty (headroom). Formulating the problem in this way allows it to be solved with an optimisation model using commercial mixed integer programming optimisation solvers. However, this simplification requires making certain limiting assumptions on how the problem is formulated. These are addressed below.

1. EBSD ensures each WRZ is able to endure the worst historical supply on record and meet levels of service requirements (demand) (Environment Agency, 2012). Supply and demand management schemes use annual yields (DOs) that are estimated or calculated using an external simulator run under historical drought conditions (Matrosov et al., 2013). The DOs for different schemes are then combined linearly during the optimisation. This assumes that all these schemes will contribute their DO as estimated or simulated during the one particular drought event which presented one particular spatial and temporal scarcity pattern (the drought whose conditions were used to estimate the DO). This assumption works well for hydrologically independent schemes like water reuse or desalination, but may not for schemes that work together using various operational rules and triggers, for stream aquifer-interactions or for combinations of

demand management schemes. Linear combination of yields is a pragmatic assumption but it is problematic precisely under the stress conditions that test yields, when multiple sources interact in unforeseen patterns during system drought events. This assumption may result in a system that is either over-conservative or insufficient under possible future conditions.

2. EBSD models are single objective (minimisation of total aggregated economic costs). The performance of water supply systems is inherently judged by multiple criteria (e.g. service reliability, environmental performance, and energy use in addition to costs). In EBSD these criteria must be commensurated into economic costs.

3. EBSD uses dynamic annual estimates of demand. However, supply DO estimates are generally static. In reality over the simulation time-horizon, yields may change or fluctuate with climate, natural hydrological variability and land-cover/land-use practices.

4. EBSD assumes that each year's storage supplies are unrelated to the previous year's storage levels. This assumption is not appropriate for areas where over-year storage is significant. In such cases more complex formulations are required to track storage levels and other water management variables, e.g. at the monthly level, are necessary (Loucks et al., 1981).

5. EBSD strives for optimality under historical stress conditions and does not seek robustness. EBSD cannot consider multiple scenarios (e.g. climate perturbed hydrologies) and produce a 'low regret' plan that is robust across all of them. Instead it can optimise over multiple simultaneous scenarios (e.g. such as the two demand scenarios in this study (Appendix), but it will select schemes that satisfy the most stringent supply deficit (for any given WRZ in any given year) rather than plans that satisfice performance over all scenarios simultaneously.

6. Target headroom, which serves as a reliability constraint in the optimisation, is determined for a given level of water supply reliability for each WRZ ('level of service'). If the planning problem were repeated for a different level of reliability, the whole analysis would have to be done from scratch as it would involve re-estimating yields (DO) based on the different reliability constraint. This makes it difficult to determine the reliability vs cost trade-off with the EBSD optimisation method.

The main benefits of the EBSD framework are that 1. it is able to consider a number of possible supply and demand options and 2. in addition to the least-cost portfolio, the frameworks results provide the least-cost annual schedule of implementation of the selected options (i.e. year that options are built). The RDM application does not provide options scheduling. In the application described in the Appendix, 190 demand management and 154 supply options were considered. The model converged quickly (3 minutes on a 2-GHz laptop).

4.5.1.3 Benefits and limitations of the RDM implementation as compared to EBSD

Rather than searching through all possible plans, RDM starts from a pre-selected group of viable plans. The approach uses scenario simulation filters through these plans to reach a preferred alternative whose weaknesses are then identified by finding scenarios under which system performance needs further improvement. The following limitations of this RDM application are identified:

1. A capacity expansion model such as the EBSD model applied here selects from amongst millions of different plans: all feasible unique combinations of schemes and their different timings of implementations. In the RDM application 240 portfolios were initially vetted, a large number but still only a small fraction of the available alternate plans implying some of the better portfolios may have been missed. RDM considers planners have a small number of pre-selected preferred alternatives and these are the best starting point for a planning study. In England and Wales a water company starting with just a few preferred alternatives would likely be challenged by regulators. After an initial vetting only one (in this case) or a few preferred alternative(s) are analysed in detail rather than all 240. This underlines how RDM offers an in-depth assessment but is too detailed of an approach for cases when large numbers of alternatives should be considered.

2. Most limitations of the RDM implementation to the Thames system stem from compromises made to make the problem solvable within this study's chosen computational limits (simulations should take less than 24h on a single computer). This required limiting the number of alternative plans considered ('portfolios' of supply and demand management measures) and limiting the dimensions of uncertainty. The RDM application required 924,000 system simulations. Adding a new dimension or more supply demand options would significantly increase the number of simulations required. Adding another dimension of uncertainty with ten samples would increase the solution space to 9,240,000 simulations. The need to decrease the number of model runs required considering only a subset of supply and DM options and prevented the consideration of partial implementations of demand options. The 240 initial portfolios considered contained different combinations of 5 supply and 5 demand management strategies, a far cry from the 190

DM options and 154 supply-side options considered by the EBSD model. When considered in the RDM study each DM option was activated in every WRZ and at its fullest extent. This discouraged options whose full implementation was disproportionally expensive; such as active leakage control (ALC). A partial implementation of ALC would likely result in improved overall performance but given constraints this was not possible in this study.

3. Different plans in RDM can consider alternate timings of implementing various schemes but this will strongly increase the number of simulations performed. Each different sequence of actions or different rules to launch actions will be considered a different alternative to be tested under the plausible futures. This study only considered how portfolios would perform under conditions estimated for 2035; there is no consideration for when different schemes are brought in or how supply and demand change over time. The simulation model as used in this study was dynamic only in its consideration of hydrological uncertainty.

4. Limitations 2 and 3 above point to RDM's tendency for computational intensity. This implementation of RDM was only partial, a full application of the framework involves many more simulations in the iterative refinement phase. To counter this, a more efficient sampling scheme in lieu of enumeration could be tested.

RDM as applied in this study also offers several benefits. The objective is to identify a 'robust' plan which, although not 'optimal', performs well under a many possible futures. The benefits of the RDM application detailed further below include: multiple measures of performance are considered, the effect of multiple dimensions of uncertainty is evaluated, and that complex and nonlinear interactions between different supply and demand management schemes are explicitly simulated.

Using a simulation model allows planners to seek performance in multiple categories; a common monetary unit of measure was not required as it was under the economic optimisation approach. The RDM study allowed for planners satisfying multiple benefits: preserving environmental flows whilst improving engineering reliability and robustness in addition to keeping infrastructure and operating costs in check. By using scenario simulation RDM simultaneously considers multiple sources of 'deep' uncertainty and identifies how these sources of uncertainty come together to stress the system being designed. The treatment of uncertainty in RDM produces actual distributions of tangible performance measures that affect customers and regulators. EBSD incorporates uncertainty with regionally aggregated distributions of option yields encapsulated in a safety factor ('target headroom'). Finally with RDM a trusted system simulator is used rather than a parsimonious optimisation which extracts the essence of the problem but does not make assessments based on detailed evaluation of the actual performance of the portfolio of schemes under plausible conditions. A simulation approach for example allowed considering time-varying management features such as seasonal tariffs and non-linear management procedures such as water conservation or rationing triggers, the LTCD operating rule (Figure 3.8) , and complex rules directing the activation of conjunctive use and desalination schemes.

4.5.1.4 Recommendations

Currently English water companies use the EBSD framework to plan and justify investments to regulators. Using EBSD involves a 2-step process of simulating each proposed option with detailed simulators to arrive at a safe yield ('DO') estimate, then aggregating those yields linearly to find the least cost schedule of investments to satisfy future demand estimates. An important limitation of the EBSD method is the inability to consider tangible measures of performance (e.g. frequency, magnitude and duration of supply shortfalls in addition to costs, energy intensity and environmental performance) over multiple equiprobable futures, such as UKCP09 climate change scenarios (Murphy et al., 2009).

In practice joint use of both frameworks may offer a better chance at effectively planning water resource systems than using only one. EBSD requires significant simplification of system performance whilst simulation under uncertainty approaches such as RDM require reducing the set of considered portfolios. This suggests joint use of the two methods could make up for their individual deficiencies. To initially consider all alternative designs (rather than an arbitrarily chosen one) EBSD optimisation could be used as the initial step of the RDM framework which aims to identify one or more candidate strategies. The concern there would be that the limitations of EBSD would bias the RDM starting point, i.e. the preferred alternative. To help remediate this, an EBSD analysis could be run under several future conditions (e.g. benign, moderate and dire future scenarios) each leading to a candidate strategy.

The candidate strategy or strategies would then be submitted into the vulnerability characterisation step of the RDM framework by using a simulation model to estimate performance of the strategy under many future scenarios to uncover its vulnerabilities.

Joint use of the frameworks would allow detailed multi-criteria and probabilistic investigation of the least-cost portfolios and would allow further incremental improvement of proposed strategies through RDM. Improving the EBSD-chosen strategy through successive RDM iterations would result in exchanging some optimality for robustness to future uncertainties. Because this implementation of the RDM framework did not incorporate scheduling, a separate scheduling routine would need to be run after the robust portfolio is developed through RDM.

4.6 Conclusion

In this chapter Robust Decision Making was used to evaluate the Thames basin water resource system planning problem. Regret analysis was used to choose a candidate strategy after simulating water resource system portfolios under a wide-range of possible future hydrologies, demand levels and energy costs. The vulnerabilities of the candidate strategies were then identified using a statistical data mining algorithm. When compared to the current planning framework in England and Wales (EBSD) which uses an aggregated economic optimisation approach, RDM's advantages are that it uses a more realistic simulation model that can output performance in multiple performance criteria and it plans for robust strategies under conditions of 'deep' uncertainty rather than one that is optimal for a single future. This, however, severely limits the total number of possible future options RDM consider. This limitation led to the recommendation to use both frameworks in conjunction with EBSD being used to narrow down the total number of portfolios to consider. RDM can also be used together with other decision making frameworks such as Info-gap Decision Theory which is the focus of the next chapter.

5 RDM comparison to Info-Gap Decision Theory

5.1 Introduction

In this chapter Robust Decision Making (RDM) was compared to 'Info-Gap Decision Theory' (Info-Gap). Similar to RDM, Info-Gap Decision Theory (reviewed in Section 2.3) uses trusted simulation models to consider a wide spectrum of plausible futures each with different input parameters to represent uncertainty. Info-gap is a tool that compares potential strategies' performance under a wide range of plausible futures and quantifies their robustness and their potential for rewards (opportuneness) under favourable and unfavourable future conditions. In Info-gap uncertainty is characterised as a set of nested sets centred around the best estimates of uncertain parameters. The performance of potential strategies is then calculated using a simulation model as the value of input conditions successively deviates from the best estimates. The maximum amount of deviations before the strategy fails to perform satisfactory is termed its 'robustness'. Info-gap is reviewed in detail in Section 2.3.

In a recent comparison of the two approaches, Hall et al. (2011a) highlight the strengths of IGDT and RDM for robust system planning. In their application they find both tools come to similar conclusions to a climate change problem but provide different insights about the performance and vulnerabilities of the analysed strategies. Since both methods are broadly similar (Hall et al., 2011a) most analysts will use either one. This study shows that using only one of these methods can lead to missing important information that could have been uncovered if both frameworks had been used. Joint application reveals complementary information that would not be available if only one method were implemented.

5.2 Info-Gap Decision Theory analysis

5.2.1 Info-gap problem formulation

The Info-Gap analysis (Section 2.3) begins with a similar problem formulation to the one supply only RDM study presented in Section 4.3. The same infrastructure portfolios composed of the same supply options listed in Table 4.2 and Table 4.3 were used in this analysis along with identical costs and release rates (Table 4.4).

5.2.1.1 Uncertainties

Info-Gap assumes that the uncertainty of the system is defined as a group of nested sets defined by the best guess or central estimate, *u,* of an uncertain parameter. Deviations from the central estimate, $\tilde{u}$, are scaled by the 'horizon of uncertainty', *h,* (Figure 2.1). This forms the Info-Gap uncertainty model $U\ (h, \tilde{u})$.

Uncertainties considered in both studies include hydrological variability, climate change flow perturbation, London demand and energy prices. To be able to be used in the Info-gap uncertainty model, the uncertainties used for the RDM study (Section 4.3.2.1) with the exception of the hydrological variability, which is characterised by the historical surface flow time series, must be adapted. The uncertain parameters to be adapted to the Info-gap study include water demand, the price of energy and climate change hydrology.

In the RDM study, a gamma distribution with shape 311 and scale 6.9 was used to represent demand projections for 2035 (Section 4.4.3). The Info-Gap analysis requires a point estimate of demand. The median of this gamma distribution is used to be this estimate for the water demand in 2035, Y|x = 0.5 (2144.5 Ml/day). The deviations from this central estimate also derive from the underlying gamma distribution such that: x = 0.525, 0.550, 0.575, . . . , 0.975. The gamma distribution was also identically sampled to the left of the median as it was to the right. Sampling on the left results in lower demand and thus more favourable future conditions while sampling on the right results in higher demand.

The RDM study considered climate change uncertainty by using an ensemble of 100 monthly flow factors to perturb historical flow. The central estimate (median) of this flow factor set is used as the best estimate for Info-gap. Ensembles of monthly perturbation factors then diverge from the median flow factor set at structured intervals as defined by the Info-gap uncertainty model. The flow perturbation factors are applied to the historical flow time-series and do not take into account possible shifts in the hydrologic regime, furthermore the hydrological consistency of the scaled Info-Gap climate time series has not been verified. The uncertainty parameters for the Info-Gap model and how they compare to those of the RDM analysis are summerised in Table 5.1.

A uniform distribution of price estimates (£0.09- £0.22/kWh) was assumed based on current energy price (£0.09) (Eurostat, 2011) assuming prices will increase (Department for Energy and

Climate Change, 2010). A uniform distribution was assumed as insufficient data on any other probability distribution was available. For the RDM application the uniform distribution was divided into 13 equiprobable intervals whose boundaries were used to produce 14 energy costs. For the Info-Gap study a best estimate of 13 p/kWh was used to construct the uncertainty model bounded by the upper and lower estimates described above.

Using these uncertainties the uncertainty function is formally defined:

$$U(h,\tilde{u}) = \{u\colon \max[\sigma_l\,, (1-\kappa_l h)\tilde{u}_{i,j}] \leq u_{i,j} \leq \min[\,\sigma_r, (1+\kappa_r h)\tilde{u}_{i,j}]\}\ h \geq 0, i = 1,2,3\,, i = 1, 1-12 \quad (8)$$

where:

u_1 ,u_2,, u_3 represent climate change perturbation, water demand and energy cost uncertainty respectively

κ_l = [0.005, 0.0125, 0.1] and are scaling factors for the left hand side of the Info-Gap model for u_i

κ_r = [0.005, 0.0125, 0.25] and are scaling factors for the right hand side of the Info-Gap model for u_i

σ_l = [1.2, 1914.81, 9] and are the lower boundaries of the Info-Gap model for u_i

σ_r = [0.8, 2391.88, 22] and are the upper boundaries of the Info-Gap model for u_i

Using scaling factors for the deviation from the central flow factor set compresses or extends the seasonal range of flows of the best estimate scenario. Scaling factors that are less than one result in lower flows whilst a scaling factor that is greater than one results in higher flows. A total of 40 intervals of uncertainty either side of the central estimate are used for each uncertainty dimension. Each uncertainty dimension must use the same number of intervals. Using more intervals on each side of the central estimate would result in smaller differences in system performance between intervals while using fewer intervals would result in a coarser analysis; 40 intervals was deemed to be a good balance between the resolution of the horizon of uncertainty and the change in performance resulting from moving one interval away from the central estimate.

Table 5.1 Uncertain system parameters for strategic water resource forecasting in the Thames Basin for the 2020–2035 planning horizon.

Parameter	RDM	Info-gap
Hydrological Variability	Historical flows[1]	Same as for RDM
Climate Change Perturbation	100 monthly flow perturbation sets valid for 2020-2035[4] (Monte-Carlo sampling)	A single central estimate climate change flow factor set[2] with 40 intervals of uncertainty either side of the central estimate
Water Demand	11 water demand levels obtained using LHC sampling of deciles of a gamma distribution + 2 extreme values from distribution forecasts [3]	A single central estimate of demand with 40 conditional intervals of uncertainty scaled by the gamma distribution either side of the central estimate[3]
Energy Prices	14 energy prices [4] obtained using LHC sampling of 13-quantiles of a uniform distribution	A single central estimate with 40 horizons of uncertainty either side of the central estimate[4]

[1]NRFA [2](UKWIR, 2009) [3] (Thames Water, 2010) [4] (Eurostat, 2011)

5.2.1.2 Performance metrics

Similar to RDM, Info-gap requires performance metrics that are used to designate a simulation run a success or failure. Info-gap performance metrics are analogous to those that are used in the RDM study and have the same limitations (i.e. simple metrics are used to illustrate the decision-making framework). The same RDM demand reliability, reservoir susceptibility, cost, environmental and energy performance criteria are applied to the Info-Gap formulation and determine if a simulation is a success or failure (Section 4.3.2.2).

This problem formulation was used to perform both the Info-gap robustness and opportuneness analyses.

5.2.2 Robustness analysis

As described in Section 2.3, the generic Info-gap model describes the robustness of a solution (q_i) , $\hat{h}$, as the maximum number of deviations from the central estimate that can be tolerated whilst still achieving a level of performance Π that is greater than a threshold value level Π_c:

$$\hat{h}(q_i, \Pi) = \ max\left\{h\!: \min_{u \epsilon U(\alpha, \widetilde{u})} R(q_i, u) \geq \ \Pi_c\right\} \tag{9}$$

The robustness function of this infrastructure selection study is defined using the problem formulation described above:

$$\begin{aligned}\hat{h}\big(\Pi_c(Res_o, Cost_t, Energy_{p,} Env_{p,} Rel_{L2,L3}), q\big) \\ = \ max\left\{h\!: \left(\min_{u_i \in u(h)} \Pi_{Res_o, Cost_t, Energy_p Env_p, Rel_{L2,L3}} \ (u_{1,2,3}, q)\right)\right. \\ \left. \geq \Pi_c(Res_o, Cost_t, Energy_{p,} Env_p, Rel_{L2,L3})\right\}\end{aligned} \tag{10}$$

where:

Res_o= Storage susceptibility

$Cost_t$ = Total cost

$Energy_p$ = Total energy consumption

Env_p= Environmental performance

$Rel_{L2,L3}$= Service reliability

The robustness analysis required 780 IRAS-2010 simulations. Using the performance metrics and failure thresholds discussed in Section 4.3.2.2 each simulation was classified as a successes or failure.

Table 5.2 shows at which interval of uncertainty each infrastructure portfolio fails and which criterion it failed. IPs 1-4 failed at even the best estimate scenarios whilst IPs 5-6 only were able to perform satisfactorily for the best estimate scenario before failing the environmental performance criterion on the 1st interval of uncertainty. IPs 7-8 and 9-10 succeeded only up to the 3rd and 2nd interval of uncertainty respectively. Because of their poor robustness the first 10 IPs were not included in the further analysis.

Table 5.2 Robustness to uncertainty for IPs 1-20. Robustness is the maximum number of increments of uncertainty away from the central estimates of inflow, demand and cost for which the system maintained minimum performance requirements.

Option	Robustness	Failure Criterion
1	FAIL	Reservoir Susceptibility, Service Reliability L2 and L3
2	FAIL	Reservoir Susceptibility, Service Reliability L2 and L3
3	FAIL	Service Reliability L2 and L3
4	FAIL	Service Reliability L2
5	0	Environmental Performance
6	0	Environmental Performance
7	3	Environmental Performance
8	3	Environmental Performance
9	2	Environmental Performance
10	2	Environmental Performance
11	5	Environmental Performance
12	6	Environmental Performance
13	7	Environmental Performance
14	8	Environmental Performance
15	7	Energy Consumption
16	7	Energy Consumption
17	9	Environmental Performance
18	9	Environmental Performance
19	5	Total Cost
20	2	Total Cost

IPs 11-20 together included 90 successful simulations. Figure 5.1 shows the robustness curves for IPs 11-20. The robustness curves show the performance of each IP at each interval of uncertainty. IP 17 and 18 are the most robust as they are able to withstand 9 increments of uncertainty. The 9th increment of uncertainty represents a scenario that is 5% drier than the best estimate climate scenario and has a water demand of up to 2179Ml/day and an energy cost of 15.25p/kWh.

IP 14 is the next most robust option and is able to meet minimum performance at up to 8 increments of uncertainty translating to a future that is 4.5% drier than the best estimate with a demand of up to 2175 Ml/day and an energy cost of up to 15p/kW. IPs 13, 15 and 16 are successful up to 7 increments of uncertainty (4% dryer, demand up to 2172Ml/day, energy cost 14.5p/kWh). IPs 13, 14, 17 and 18 fail the environmental performance metric, whilst IP 15 and 16 fail because of high energy consumption.

Greater investment does not necessarily mean a more robust strategy. This can be seen for IPs that include DESAL140 which is characterised by high energy consumption and therefore high operating costs. This makes IPs 15 and 16 fail the cost criterion. IPs 19 and 20 include DESAL140 and the RST, both of which have high operating costs. These IPs fail the cost criterion early despite the fact that they are capable of providing large amounts of water during droughts. IPs 19 and 18 do not fail the cost criterion as they only include DESAL80 resulting in lower operating costs.

Figure 5.1 shows the robustness curves of the selected IPs. The robustness curves for environmental performance, total costs and energy consumption are relatively linear. This is a result of the relatively linear relationship these performance criteria have with water availability and demand. Steep robustness curve gradients reveal that there is little performance loss with large deviations from the central estimate. Crossing robustness curves occur at points where one IP becomes more robust than another. This can be seen in the storage susceptibility and service reliability criteria (Figure 5.1 a and d respectively) which have non-linear robustness curves. These criteria depend on the time of year and the storage in the aggregate storage node (LAS) (Table 4.1). There are instances in the simulation when conditions get so harsh that water use restrictions are implemented sooner. This results in more weeks spent in failure (decreasing service reliability) but an improvement in storage susceptibility as compared to the previous interval of uncertainty. This relationship can be seen in Figure 5.1 b and c for IP 19. A considerable improvement in the storage susceptibility metric at interval 8 can be seen and is paralleled by a reduction in L2 and L3 service reliability at the same two increments.

Because they have RST and DESAL140 and therefore can provide large amounts of water during droughts, IPs 19 and 20 perform better than IPs 13-18 in the reservoir susceptibility metric at each increments of uncertainty. They however, fail after 5 and 2 increments of uncertainty in the cost metrics as a consequence of their high capital and operating costs.

Crossing robustness curves reveal important information about the infrastructure portfolio. IPs 17 and 18 have steeper robustness curves than IPs 15 and 16 signalling that they are less affected by worsening conditions. Because they begin with a lower reservoir susceptibility performance, they perform worse than IPs 15 and 16 until the 6^{th} interval of uncertainty. At the 7^{th} interval, the robustness curve for IP 18 crosses that of IP 15 and for subsequent intervals of uncertainty it continues to be more robust. The robustness curve for IP 15 crosses that of IP 17 at the 8^{th} interval. Crossing robustness curves can also be seen in the reliability performance criteria however, the crossings are oscillatory and therefore this does not denote a permanent shift.

IP 14, (UTR150, DESAL80 and SLARS), is one increment of uncertainty less robust than IPs 17 (RST, DESAL80) and 18 (RST, DESAL80, SLARS). This IP is still an infrastructure heavy option, but it does not possess the almost limitless capacity of the RST to maintain supplies. This slightly decreased robustness in this criterion increases its robustness in the cost criterion as it has lower capital and operating costs than IPs 17 and 18 (Figure 5.1 c). IPs 17 and 18 still outperform IP 14 in environmental performance, service reliability (L2 and L3) and storage susceptibility.

IPs 14, 17 and 18 are shown to be the most robust strategies and reveal that there is a trade-off between robustness in service reliability, environmental performance and storage susceptibility and total costs and energy consumption.

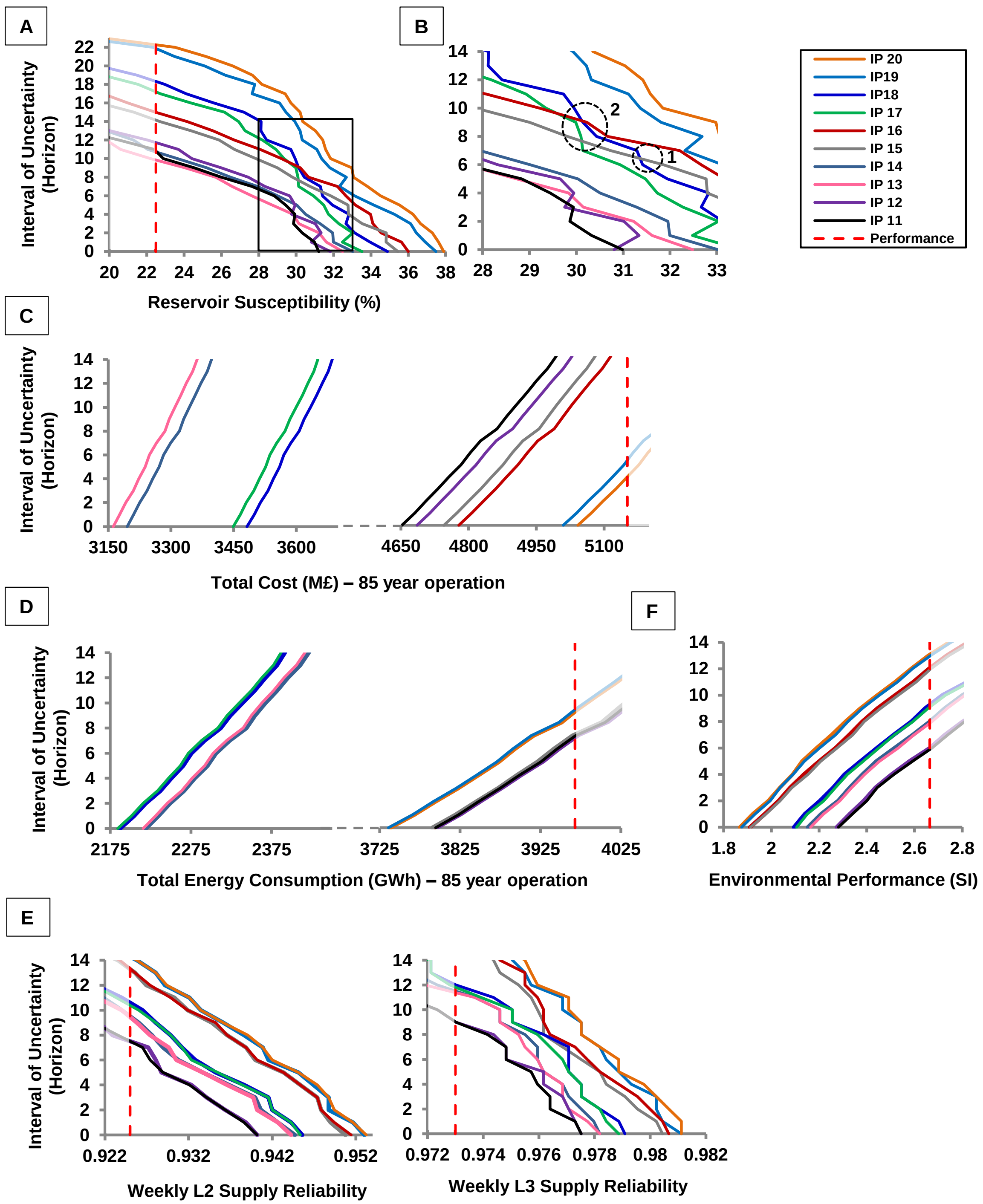


Figure 5.1 Robustness curves for IPs 11–2 for storage susceptibility (a and b), cost (c), energy consumption (d), service reliability (e) and environmental performance (f). Results show that for cost, energy and environmental performance there is a linear decrease in performance with increasing demand and decreasing water availability. Storage susceptibility has crossing robustness curves (1 and 2 in A). Where curves cross at 1 (b), IP 18 becomes more robust to uncertainty than IP 15. At 2 (b) the same occurs for IP 17 and IP 18; they both become more robust than IP 16.

5.2.3 Opportuneness Function

The opportuneness function equation asks the opposite question as the robustness function: what level of performance windfall does the strategy achieve if conditions are more benign than expected (the right side of the Info-Gap uncertainty model)? The opportuneness function is the inverse of the robustness function and quantifies the level of performance reward in (Π_R) in each of the performance criteria as the scenarios become increasingly wetter, with lower demand and energy costs.

$$\hat{\beta}\left(\Pi_r(Res_o, Cost_t, Energy_{p,}Env_{p,}Rel_{L2,L3}), q\right) = min\left\{h: \left(\max_{u_i \in u(h)} \Pi_{Res_o,Cost_t,Energy_p Env_p,Rel_{L2,L3}}\ (u_{1,2,3}, q)\right) \geq \Pi_r(Res_o, Cost_t, Energy_{p,}Env_{p,}Rel_{L2,L3})\right\} \quad (11)$$

Opportuneness analysis can help decision-makers choose between similarly robust strategies. The opportuneness analysis was performed for IPs 14, 17 and 18 and included 40 simulations for each. Similar to the robustness analysis, curves can be plotted showing the performance of each option in each criterion. In the opportuneness analysis the lowest curves with shallow gradients are preferred as these strategies display high performance rewards for small increments of uncertainty. Crossing curves show when one strategy gives greater reward than another after a certain increment of uncertainty.

Figure 5.2 shows the opportuneness and robustness curves for IPs 14, 17 and 18 for each of the performance criteria. Robustness curves are included in order to better recognize trade-offs between robustness and opportuneness. The environmental performance, cost and energy consumption criteria show a relatively linear relationship with increasing uncertainty. Service reliability L2 and L3 show step changes in reward but they do not result in crossing curves.

Since none of the opportuneness curves cross, the IPs can be easily ranked. IPs 17 and 18 give similar levels of reward and in general give more reward than IP 14 in all criteria except for cost. This greater cost reward IP14 however does have a trade-off with lower overall robustness.

The Info-gap analysis identifies IP18 (RST and DESAL80) as the preferred infrastructure portfolio. IP 18 performs better than IP 14 in all criteria except for cost at each increment of uncertainty. IPs 17 and 18 are similar; IP 17 is more opportune to cost uncertainty but IP18 outperforms IP 17 for all other criteria.

The Info-gap analysis selects IP 18 as the preferred plan for a conservative planner. If less deviation from the future best estimate were to occur IP 14 would be more appealing for its robustness to cost increases in harsher futures and greater cost rewards in more benign futures.

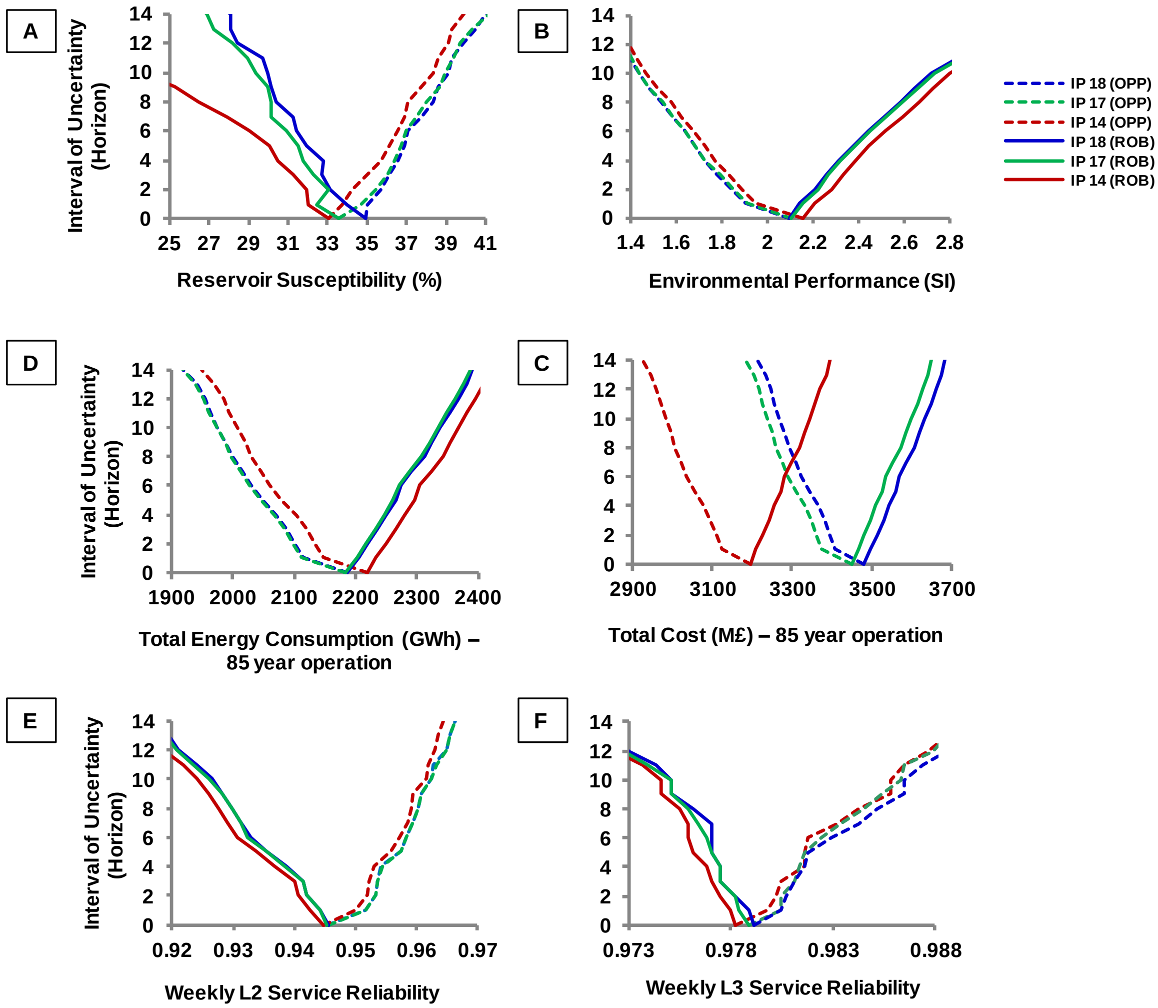


Figure 5.2 Opportuneness curves (dotted lines) for IPs 15, 16, 17 and 18 for reservoir susceptibility (a), environmental performance (b), cost performance (c) and energy consumption (d) and service reliability at L2 (e) and L3 (f). The results show relative linearity between improvements in each performance measure and each successively more benign future. Robustness curves are also included to aid analysis of possible trade-offs (solid lines). Results show that performance rewards are comparable between the options except for total costs where IP 14 shows significant cost rewards (reductions) compared with IPs 17 and 18. These cost rewards are combined with lower rewards in the remaining performance metrics.

5.2.4 Info-gap results discussion

The Info-gap analysis is implemented using the fractional error Info-Gap model (Equation (4.1) which characterised the uncertainty in input parameters and structured an interval-based approach to incrementally sample harsher and more benign futures away from the central estimate.

Info-gap samples the uncertainty space using the vector *h*. The three uncertain system parameters (inflows, demands, energy costs) are scaled concurrently, either becoming increasingly harsher or more benign in the case of robustness and opportuness respectively. For instance, hydrology becomes drier whilst demand and energy cost increase. Such sampling leads to fewer simulations as not all combinations of input parameters are enumerated: only 40 simulations for each IP rather than an enumeration of 64,000 simulations for each IP (40 inflow, 40 demand and 40 energy intervals) as in the case of RDM. This can lead to a potential draw-back as this fractional-error Info-gap approach does not consider cases where for instance demand decreases whilst energy costs increase or where demand decreases whilst hydrology becomes drier (vulnerable conditions as show by RDM's vulnerability scenario 2).

According to the Info-Gap analysis, IP18 is the most robust infrastructure portfolio and is able to satisfice performance criteria for futures that are up to 5% drier with demand reaching 2179 Ml/day and energy costs rising to 15.25 p/kWh. IP18 is able to meet minimum performance requirements, including London supply reliability, for the greatest number of uncertainty intervals from the central estimate up until it fails in the environmental performance criteria.

The plotting of robustness curves allows comparing the performances of different IPs in each performance criterion at different intervals of uncertainty around the best estimate. This plots demonstrate that IP18 is the most robust to uncertainty in the storage susceptibly, service reliability and environmental performance metrics. Furthermore, the steepness of the robustness curve in the storage susceptibility metric shows that there is less performance loss at each interval of uncertainty when compared to IPs 15 and 16. IP18 becomes more robust to uncertainty than IP 15 and IP 16 at points 1 and 2 in Figure 5.1b. This change in robustness is a consequence of the complex interactions between the emergency supply infrastructure, environmental flow and demand reductions as governed by the LTCD.

The Info-gap analysis also reveals that IP14 is also a good strategy. Its robustness and opportuness show that if the decision maker could be more certain the future will not diverge greatly from the central estimate (or be more benign) then IP14 would be more preferable because of its improved cost performance.

5.2.5 Complementarity of RDM and Info-gap

Both RDM and Info-gap helped assess the robustness of 20 different water supply infrastructure portfolios (IPs) to Knightian or 'deep' uncertainty in hydrological inflows, water demands and energy costs for the year 2035. Due to differences in their approaches they reached similar but not entirely matching results. Info-gap promotes IP 18 as the infrastructure portfolio of preference whereas RDM initially suggests IP 14 (Section 4.3.3.1). This observation leads to the main finding: because RDM and Info-gap provide planners with different and complementary information they can beneficially be used together. Joint use of Info-gap and RDM for the planning of water resource systems is recommended as each method can help clarify the results of the other.

Info-gap begins with a best estimate for each uncertain system input and then sequentially chooses values increasingly farther away from expected inputs. The best estimate of future conditions that was used has a greater disparity between winter and summer flows, higher water demands and higher energy costs than the historical average. As a result the Info-gap analysis, even at a zero interval of uncertainty, begins with the system that is under considerable stress before it considers less or more favourable conditions.

RDM samples from all combinations of the uncertain system parameters to identify conditions of system failure. RDM samples the 'extreme' futures as in Info-gap but also more benign ones. In both Info-gap and RDM, the robustness of simulated futures is assessed using multiple criteria such that IPs that are less infrastructure intensive (less costly and energy intensive) outperform more infrastructure intensive IPs in benign future states. These benign future states are taken into account during RDM's initial regret analysis and reduce the multi-criteria regret values of less infrastructure intensive options that perform reasonably well in the storage reliability, storage susceptibility and environmental categories. Info-gap does not consider these more benign futures and therefore less infrastructure intensive IPs do not perform well. For more benign futures, IP 14 has a lower median regret than IP 18, the more infrastructure intensive alternative (Figure 4.2 a) whilst for more dire futures (Figure 4.2 b), which more closely relate to the futures sampled in Info-gap (Table 5.1), IP 18 performs better. When only considering harsh futures, Info-gap and

RDM recommend the same future plan. Indeed, RDM's vulnerability scenario 1 (Table 4.7) shows IP14 is vulnerable to failure under conditions that are only slightly harsher and even sometimes more benign (in the demand uncertainty dimension) than those that define the best estimate for the Info-gap analysis.

Because Info-gap assesses robustness of each option under progressively more dire futures, there is a tendency to favour IPs with infrastructure-intensive solutions. Using Info-gap, it is difficult to jointly consider information about an IP's robustness to uncertainty and opportuneness for a performance reward. The regret analysis in the RDM implementation produced a single plot to characterise performance across all futures (Figure 4.2). In this way RDM provides complementary information to an Info-gap analysis on the suitability of future plans across a range of dire, benign and opportune futures. The RDM application found solutions that are robust over a wide range of future states whilst the Info-gap analysis identified solutions that are robust over dire futures and opportunistic over favourable futures. Taking into account the robustness of IPs for mild futures in water planning studies helps prevent decision makers from automatically favouring conservative (in this case infrastructure intensive) options. At the same time Info-gap underlined the fact that the preferred option under RDM was quite vulnerable to dire futures.

Info-gap robustness curves provide decision makers with useful visualisations that complement an RDM analysis. By plotting the performance of each option for each metric at each increment of uncertainty, trends in performance under increasingly dire or favourable conditions are revealed. This was seen for example in the service reliability performance criteria for IP 18 (Figure 5.1 a and b): initially IP 16 performs better but as conditions get worse IP 18 improves revealing it performs increasingly better under harsher conditions relative to IP 16. The Info-gap plots show choosing IP 18 over IP 16 results in a cheaper and less energy intensive (Figure 5.1 c and d) system in harsher futures. Info-gap robustness analysis also shows which performance criterion each IP fails at first whilst RDM does not track the model of failure. In this way environmental performance may be considered as a 'soft' performance rule which in reality could be reduced temporarily during droughts. Info-gap revearls that under very harsh conditions, IP 18 fails environmental performance first, but if this is a shifting goal-post during droughts, IP 18 would still be acceptable (i.e. service reliability is not the first requirement to fail under harsh conditions).

The sampling in RDM meant a wide range of dire, benign and favourable conditions were considered during plan evaluation. RDM's scenario discovery approach identified the vulnerable sets of uncertain conditions for the preferred plan. These vulnerability scenarios were then used to check if other infrastructure portfolios could actually perform better under the rough conditions. The RDM application showed IP 18 was the most robust option for more severe conditions; this was the preferred option from the Info-gap analysis.

The RDM implementation required 311,080 simulation runs and Info-gap 1600 simulations. The supplementary runs required for Info-gap suggest it is worthwhile to consider joint application. For example Info-gap could be used along-side regret analysis to identify the initial candidate strategy, or to propose an alternative one for analysis in RDM's scenario discovery phase. Also, Info-gap can be used to thin out the option sets considered in RDM; this could be useful when there are many possible initial options or plans. Info-gap assumes analysts can provide a best estimate around which the uncertain parameter is assumed to lie and therefore does not explore the full the uncertainty space. Complementing an Info-gap approach with another such as RDM which samples future conditions more widely was found to be an effective guard against potentially missing critical design conditions. Info-gap can effectively be used to explore local robustness around selected scenarios in the uncertainty space. It should be noted that this discussion is based on one case study. Other benefits and limitations of Info-gap and RDM could be revealed through further studies.

The overarching benefit of using RDM and Info-gap methods is that they provide a structured approach to simulating systems under Knightian uncertainty. The methods select relevant system conditions to simulate and reveal how different plans perform under these conditions. Joint use provides widens the insights gained and helps verify and deepen the understanding that arises from using either method.

5.3 Conclusion

This chapter compared the RDM framework to Info-Gap Decision Theory. Both frameworks are scenario-based simulation planning methods that seek robust rather than optimal solutions. When comparing to Info-gap it was shown show that although the methods initially provide different capacity expansion recommendations, they produce broadly similar results but provide complementary information about the performance of different proposed infrastructure portfolios. Joint use of Info-gap and RDM for the planning of water resource systems helps better understand the results of each method. Info-gap efficiently evaluates system performance under different supply and demand management options considering the most dire and opportune future conditions. The framework identifies which criteria cause failure of a future plan and allows plotting the performance of each option as future system inputs progressively deviate from an initial estimate. It may however ignore parts of a Knightian uncertainty space if the initial estimate ends up not being accurate. RDM samples a wider set of combinations of the uncertain variables allowing a more holistic, albeit more computational intensive assessment of the future performance of different plans. Through RDM's scenario discovery combinations of uncertain inputs that lead to system vulnerabilities are identified. Regret analysis efficiently quantifies how different future plans fare over the vulnerable scenarios considering multiple performance criteria. RDM provides a structured framework for iterative refinement of future plans. Both methods offer structured and insightful frameworks to plan complex systems with multiple requirements subject to multiple unknown future stresses. Joint use of the methods can make them more computationally efficient and maximise understanding by revealing how each method can skew results towards particular future plans. RDM and Info-gap can be used by decision makers to produce strategies that are robust to future uncertainty and provide decision relevant information about these strategies, however, these methods cannot consider a large number of possible future options in practice as they are computationally burdensome. In the next chapter a method that combines simulation with many-objective optimisation is used to improve upon this limitation and also provide further insight into the planning problem by visually analysing the trade-offs between the multiple performance objectives.

6 Many-Objective Optimisation and Visual Analytics

6.1 Introduction

In the previous two chapters Robust Decision Making and Info-Gap Decision Theory were used to find robust water resource management plans for the Thames basin. Both of these frameworks considered 'deep' uncertainty in future conditions by simulating the system under a wide range of plausible futures. A detailed simulation model was used to measure the performance of the system for each future with multiple performance criteria. The main limitation of RDM and to a lesser extent Info-Gap, is that they are computationally burdensome and as a consequence they cannot consider a large number of strategies. This is a problem for water companies that need to consider many possible supply and demand management options as is typically the case in in a regional water resource system planning problem. A similar infrastructure selection problem (discussed in the Appendix) was solved with the Economics of Balancing Supply and Demand (EBSD) framework, the current planning framework in England and Wales. The EBSD method was able to consider a far greater number of supply and demand management options and their combinations. However the EBSD framework has its own limitations, mainly stemming from its use of an aggregated single-objective optimisation model which is spatially and temporally aggregated and does not the capture the detail of the water resource system and does not consider the inherently multi-objective nature of the planning problem. In Section 2.4 the limitations of lower dimensional optimisation with aggregated optimisation algorithms were discussed in detail and many-objective optimisation using evolutionary algorithms was further reviewed in Section 2.5.4.

In this chapter the London supply and demand management portfolio selection problem formulation for the year 2035 is presented and considers more supply and demand management options and many more of their combinations. This planning problem is solved using a multi-objective evolutionary algorithm linked to the Thames basin IRAS-2010 model. This combined optimisation/simulation framework allows the consideration of significantly more plans than the RDM framework but still allows the use of a simulation model retaining the level of detail that simulation allows. The use of a simulation model and a multi-objective evolutionary algorithm allows the performance of the system to be measured in multiple performance criteria. The output of this approach includes multi-dimensional trade-off plots that decision makers and stakeholders can use to better understand how portfolios in multiple-performance criteria.

This study investigates the trade-offs revealed by a many objective optimisation approach to planning future Thames basin infrastructure and demand management options as revealed by many-objective optimisation. The term “many-objective” refers to optimising systems with 4 or more design objectives as introduced by Fleming et al. (2005). Optimal portfolios (mixes) of different schemes are evaluated according to their performance across a range of measures (economic, engineered, and ecological). The addition of objectives into the planning exercise was shown to reveal information that is hidden when only one or two objectives are considered. The trade-offs generated by the many objective optimisation reveal that ecological, engineered and economic performance can be improved with relatively modest investments. Trade-off visualisation reveals how similar schemes may cluster in certain areas of the trade-off, or Pareto, space. Pareto optimality is defined as those solutions whose performance cannot be improved in any single objective without degrading their performance in one or more remaining objectives (Figure 2.2) (Coello Coello, 2005). The set of all Pareto points is referred to as the Pareto optimal set and when plotted constitute the Pareto frontier. Visualising the trade-offs and how portfolio mixes are distributed throughout the Pareto-space gives planners valuable information about the diverse array of planning options that are available for the Thames system.

Both supply and demand management options, with a wide range of capacities and impacts, are considered to meet demands in 2035. Optimal portfolios (mixes) of different schemes are evaluated according to their performance across a range of measures (economic, engineered, and environmental). The contribution of this planning approach is to reveal information that would remain hidden if the planning problem were solved with traditional lower-dimensional analysis such as the least-cost supply-demand optimisation currently used by the English water sector (Padula et al., 2013). Adding supplementary performance objectives reveals a diverse set of Pareto-optimal ‘equally best’ groupings of options which would not have been revealed through the traditional lower dimensional least-cost optimisation problem (which is used in the EBSD framework). More formally, an approximation to the set of Pareto optimal solutions is sought.

The proposed approach could contribute to an improved supply-demand planning process for English water companies where there is demand to improve the current approach. The second contribution is to demonstrate that visualising the performance trade-offs and how the schemes and portfolios of schemes are distributed within those trade-offs gives planners valuable information about what system performances are achievable and what plans can lead to those levels of performance. As reviewed by Reed et al. (2013), this study falls within a rapidly growing body of water resources literature focused on evolutionary multi-objective optimisation.

Section 6.2 presents the Thames basin portfolio selection case study. The methods and optimisation formulation is presented in Section 6.3 and Section 6.4 followed by results in Section 6.5 and a discussion in Section 6.6.

6.2 Case study: London water supply planning

This study focuses on water supply source and demand management option selection in the Thames basin considering demand levels projected for the year 2035. A combination of infrastructure expansion and demand management is likely necessary to maintain the supply-demand balance in the Thames basin. In their Water Resources Management Plan (Thames Water, 2010) Thames Water outlines many plausible supply and demand management options. In this study the seven main proposed supply options are considered: three water transfers, a reservoir, a wastewater reuse scheme, a conjunctive use groundwater scheme and a brackish groundwater desalination plant. This list includes more potential options than the RDM studies in Chapter 4. Figure 6.1 shows the Thames basin with possible supply options. Four demand management options are also considered: water efficiency improvements, increasing active leakage control, water pipe replacements and the installation of smart meters coupled with the introduction of seasonal tariffs. Please refer to Table 6.1 for a list of the supply and demand options considered.

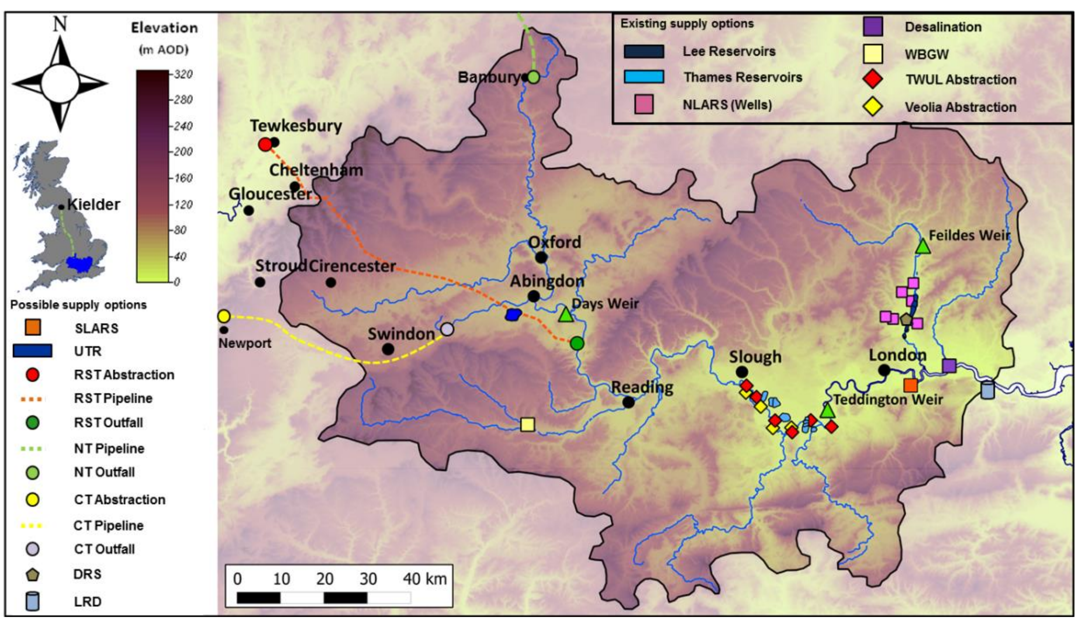


Figure 6.1 Thames basin showing the Thames basin together with the existing and possible water supply options.

Table 6.1 Possible future supply and demand options considered in this study.

Option	**Description**
Demand management options	
Active Leakage Control (ALC)	ALC refers to proactively seeking and fixing leaks in the water distribution system. Water companies consider levels of ALC implementation Higher levels result in diminishing returns: higher costs are required for the same reduction in demand.
Pipes replacement (Pipes)	Pipes includes replacement of water mains, communication pipes and supply pipes to reduce leakage in the distribution system.
Enhanced efficiency improvements (EFI)	EFI includes water efficiency campaigns, retrofitting and household and commercial customer audit programmes
Installation of smart meters with seasonal tariffs (Meters)	Meters includes installing meters in properties. Seasonal tariffs (SeTa) are based on a summer/winter trail tariff implemented by Veolia Three Valleys Water (Veolia Water Central Limited, 2010). SeTa effects on demand were calculated using the point expansion method (Griffin, 2006) to estimate the demand function at a known point on the demand curve assuming a constant price elasticity, ε, of -0.15 (Herrington, 2007).
Supply options	
Upper Thames Reservoir (UTR)	The UTR is a proposed reservoir which would release water into the Thames during times of low flow and provide constant supply to a neighbouring area.
River Severn Transfer (RST)	The RST is a proposed water transfer that would bring water from the River Severn to the Thames and a neighbouring area during periods of low flow.
Northern Transfer (NT)	The NT is a proposed water transfer that would bring water from Northern England to the Thames and a neighbouring area during periods of low flow.
South London Artificial Recharge Scheme (SLARS)	SLARS is a proposed conjunctive use groundwater recharge scheme what would function analogous to the existing NLARS.
Deepham Reuse Scheme (DRS)	The DRS is a proposed planned indirect water reuse scheme in which a proportion of wastewater from Deepham's treatment plant would undergo additional treatment and be pumped into a surface storage reservoir during drought periods.
Columbus Transfer (CT)	The CT is a proposed water transfer scheme that would bring water from the Dwr Cymru Welsh Water area to the Thames river and a neighbouring area during periods of low flow.
Long Reach Desalination (LRD)	LRD is a possible reverse osmosis treatment plant that would desalinate brackish groundwater leaking from the Thames Tideway and the Chalk aquifer underlying the Thames.

6.3 Many-objective optimisation formulation and implementation

6.3.1 IRAS-2010 Simulation model

The Thames water resource system is modelled with the open-source and computationally efficient Interactive River Aquifer Simulation IRAS-2010 (Matrosov et al., 2011) water resource system simulator. The model is an expanded version of the one used in Chapter 4. It includes 51 nodes (reservoirs, aquifers, junctions, treatment and desalination plants etc...) and 55 links (rivers, pipes, canals, water transfers). The many-objective optimisation study is performed using the Epsilon-Dominance Non-dominated Sorted Genetic Algorithm II (ε-NSGAII) which is linked to the IRAS-2010 simulator.

Demands for the year 2035 were modelled using 85 years of historical hydrology using a weekly time-step. This historical flow sequence is the same that water companies are required to use under the current accepted planning framework (Environment Agency, 2012). Estimated demands for the year 2035 were used (Essex and Suffolk Water, 2010; Thames Water, 2010; Veolia Water Central Limited, 2010).

6.3.2 Epsilon-Dominance Non-dominated Sorted Genetic Algorithm II (ε-NSGAII)

The IRAS-2010 simulator is linked via a C++ wrapper to the Epsilon-Dominance Non-dominated Sorted Genetic Algorithm II (ε-NSGAII) (Kollat and Reed, 2006) evolutionary algorithm (reviewed in Section 2.4). ε-NSGAII was chosen for its search effectiveness and efficient parallel performance (Kollat and Reed, 2006; Reed et al., 2013; Tang et al., 2006). The algorithm employs non-dominated sorting, ε-dominance archiving (Laumanns et al., 2002) and adaptive population sizing tournament selection. The ε-dominance archive sorts solutions based on the user specified levels of significant precision for the objectives (i.e., the minimum magnitude of change in the objectives that the user cares about). ε-NSGAII uses a series of connected runs between which the population size is adjusted with the introduction of new random solutions [i.e., "time continuation" see (Goldberg, 2002)]. Initially, the algorithm starts the search with a small number of candidate solutions. Over successive generations of each connected run the high quality solutions are passed into the epsilon-dominance archive. The archived solutions are injected into the population at the beginning of next run and used to automatically adjust the search population size. A quarter of this population size is comprised of the archived solutions whilst the remaining three quarters are randomly generated solutions (Kollat and Reed, 2006).

6.3.3 Optimisation formulation

The full problem formulation is described as a multi-objective optimisation function (**F**) composed of seven objective functions (*f*) with 28 decision variables (**x**) in decision space (Ω) and three constraints (*c*):

$$\mathbf{F}(\mathbf{x}) = \left(f_{\mathrm{LondVR}}, f_{\mathrm{StoTSRel3}}, f_{\mathrm{StoRes3}}, f_{\mathrm{EnvSI}}, f_{\mathrm{ResMin}}, f_{\mathrm{Cost}}, f_{Energy}\right) \quad \forall \mathbf{x} \epsilon \Omega \tag{6.1}$$

$$\mathbf{x} = (Y_i, Cap_i,)$$
$$Y_i \epsilon \{0,1\} \quad \forall \mathrm{i} \in \mathrm{N} - (\mathrm{TransRes})$$
$$Y_i \epsilon \{0,1,2,3\} \lll = \ggg \mathrm{i} = \mathrm{TransRes}$$

subject to:

$$c_{level2} : \mathrm{AnnRel}, 2 > 0.90 \tag{6.2}$$

$$c_{level3} : \mathrm{AnnRel}, 3 > 0.95 \tag{6.3}$$

$$c_{level4} : \mathrm{AnnRel}, 4 = 1.0 \tag{6.4}$$

The decisions include a binary variable Y_i that represents the decision to activate supply or demand management option *i* from the set off all options (N) at capacity *Cap*. Objectives include maximising the engineering (reliability, resilience and minimum storage) and environmental (ecological flow) performance of the system whilst minimising economic costs (capital and operating costs) and energy use. Table 6.2 summarises the formulation's decision variables: the supply and demand options and their capacities or capacity ranges. The *TransRes* set of supply option includes the mutually exclusive Upper Thames Reservoir (UTR), Northern Transfer (NT) and the River Severn Transfer (RST) supply options which are represented by decision values of 1, 2 and 3 respectively.

Table 6.2 Supply and demand options and their possible capacities included as decision variables in the study. Acronyms for option names are defined in Table 6.1

Option (*i*)	**Capacity, Cap_i (Ml/day)**	**Exclusivity or Dependence**
	Demand Management Options	
London ALC	0-50	none
London Pipes	165.1	none
London EFI	11.6	none
London MET	88.7	none
Essex ALC	0-1.36	none
Essex Pipes	3.0	none
Essex EFI	0.7	none
Essex MET	2.4	none
Central ALC	0-3.29	none
Central Pipes	4.8	none
Central EFI	2.8	none
Central MET	10.2	none
Southern ALC	0-2.08	none
Southern Pipes	1.4	none
Southern EFI	1.7	none
Southern MET	6.3	none
	Supply Options	
Upper Thames Reservoir (UTR)	133.5 - 267 to London 20 or 40 to SWOX	Mutually exclusive to RST and NT
River Severn Transfer (RST)	267 to London 40 to SWOX	Mutually exclusive to UTR and NT
Northern Transfer (NT)	74 to London 8 to SWOX	Mutually exclusive to UTR and RST
South London Artificial Recharge Scheme (SLARS)	5-19	none
Deepham Reuse Scheme (DRS)	25-95	none
Columbus Transfer (CT)	39 to London 14.8 to SWOX	none
Long Reach Desalination (LRD)	15	none

6.3.3.1 Cost Objectives

Costs include capital (CAPEX), fixed operating costs (FOPEX) and variable operating costs (VAREX). Only new supply and some new demand management options (S) incur capital costs. New and existing infrastructure as well as some demand management options (SDO) require fixed and variable operating costs. This study considers α historical 85-year long time series of inflows with demands projected for the year 2035. Operating costs are summed over each of these 85 hydrological scenarios to produce an aggregate operating cost. Scheduling is not considered in this study. All future options, if selected by the search algorithm, are activated throughout the simulation sequence. The goal is to find a portfolio of supply-demand measures that is robust to 2035 demands given a broad range of plausible hydrological conditions present in the historical sequence. No passage of time is considered in this approach so costs are not discounted. All costs are minimised:

$$\text{Minimise}: f_{Cost} = \sum_{\text{NSDO}} CAPEX_{\text{NSDO}} + \sum_{\text{SDO}} VAREX_{\text{SDO}} + \sum_{\text{SDO}} FOPEX_{\text{SDO}} \tag{6.5}$$

6.3.3.2 Engineering Objectives

The set of engineering performance objectives includes the reliability, resilience and susceptibility of the aggregate storage node, LAS. Performance on this note is quantified because it provides the majority of surface water supplies to the London WRZ and when certain LAS storage volume thresholds are breached water use restrictions in the London demand node (explained below) are imposed to reduce demand. The storage reliability objective, $f_{\text{StoTSRel,3}}$, is a temporal reliability indicator (Kiritskiy and Menkel, 1952; Klemeš, 1969) and gives the ratio of the number of time-steps the London Aggregate Storage (LAS) node (Table 4.1) was above failure level 3, (see Figure 3.8) to the total time-steps in the time horizon, N_{ts}:

$$\text{Maximise}: f_{\text{StoTSRel3}} = \left(\frac{S_t}{N_{ts}}\right) \tag{6.6}$$

In addition to indicating storage performance the storage reliability objective gives a measure of how often LTCD level 3 restrictions (hosepipe and non-essential use bans) were implemented in the basin. Level 3 restrictions were chosen to be minimised because the non-essential use ban that corresponds to the level 3 restrictions is likely to cause severe disruption to the public. Hashimoto et al. (1982) base their resilience metric on the average duration of failure. The average duration of failure ($\overline{FD_3}$) for LTCD level 3 failure events is minimised:

$$\text{Minimise}: f_{\text{StoRes3}} = \overline{FD_3} \tag{6.7}$$

A minimum reservoir storage objective (reservoir susceptibility) is defined as the lowest storage level reached (in % of total capacity) by LAS over the entire modelled time horizon. This value is maximised:

$$\text{Maximise : } f_{\text{ResMin}} = \text{MinLASVol} \tag{6.8}$$

When LAS drops below 22.5% of capacity pressure-related distribution problems occur in the network (Cookson and Weston, 2008).

Finally, the volumetric reliability gives an idea of how well the London demand was met. The London demand objective is an annual volumetric reliability metric (Kiritskiy and Menkel, 1952; Klemeš, 1969) that gives the ratio of the total volumetric shortage to the total demanded over each year. The year with the lowest annual volumetric reliability is recorded:

$$\text{Maximise : } f_{\text{LondVR}} = \min\left(1 - \frac{\sum_{t=1}^{N_{ts}} WS_{ts}}{\sum_{t=1}^{N_{ts}} WD_{ts}}\right) * 100 \tag{6.9}$$

where WS_{ts} is the time step (ts) flow shortage, WD_{ts} is the time step flow demand target and N_{ts} is the total time steps in the time horizon. The volumetric reliability gives an indication of the average deficit over the whole simulation run.

6.3.3.3 Environmental Objectives

Two environmental performance objectives are considered: 1. a measure of how well the environmental flow of the Thames is maintained and 2. the total energy consumed by water supply infrastructure over the modelled time horizon.

A shortage index for ecological flows measure is adapted from the Shortage Index (Kiritskiy and Menkel, 1952; Klemeš, 1969):

$$\text{Minimise : } f_{\text{EnvSI}} = \frac{100}{N_{ts}} \sum_{ts=1}^{N_{ts}} \left(\frac{WS_t}{WD_t}\right)^2 \tag{6.10}$$

Higher SI values signal worse performance. Because of the square in the term, larger and longer shortages will have more effect on the SI index than a sequence of smaller and shorter shortages.

SI increases when the residual flow at Teddington goes below 800 Ml/day (shaded zones in Figure 3.8). For reference, the probability of exceedence of 800 Ml/day on the Thames at Kingston is 92%

whilst for 300 Ml/day, the lowest allowable ecological flow at Teddington, it is 99% (Q_{92}=800 Ml/day and Q_{99}=300Ml/day)[5].

Energy (E) is required for pumping, desalination and treating sewage water to drinking standards. All new and existing supply nodes (*sn*) require energy to operate. Demand management measures do not require energy. The total energy consumed during a simulation is minimised:

$$\text{Minimise : } f_{Energy} = \sum_{sn} E_{sn} \tag{6.11}$$

6.3.3.4 Constraints

In their plan Thames Water state that level 2 failures should not occur more often than once every 10 years. Level 3 failures should not occur more often than once every 20 years and level 4 failures should never occur (Figure 3.8). It is assumed that even with uncertain hydrological conditions it will be possible to avoid level 4 failures given the possible new supply and demand options available. An occurrence reliability (Kiritskiy and Menkel, 1952; Klemeš, 1969) metric is used to impose these constraints which gives the ratio of the number of years that LAS did not experience a failure of level *i*, S_y to the number or years in the time horizon, N_y.

$$\text{AnnRel, i} = \left(\frac{S_y}{N_y}\right) \tag{6.12}$$

Following the above equation results in the constraints shown in Equations (6.2)-(6.4):

The algorithm implements a constraint based tournament operator where feasible solutions are always preferred to infeasible solutions. In general, simulations that do not meet these constraints are considered infeasible and are not passed into the archive of the MOEA. However, if all solutions are infeasible, the constrained tournament selection promotes solutions with the smallest aggregate constraint violations (Deb, 2001; Kasprzyk et al., 2009).

Water resource systems are complex and a variety of other performance metrics could be used to reflect the complexity of real systems. The objectives represented by the above performance metrics are determined to be sufficient to illustrate this multi-objective decision making framework but may underrepresent the full complexity of the system.

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[5] Q92 and Q99 was calculated using daily gauging records from the National River Flow Archive (1883-2010)

6.4 Computational Experiment

The ε-NSGAII generates its initial random population of decision variables by exploiting uniform random sampling within the user specified ranges given in Table 6.2. These variables are then passed as input variables to the IRAS-2010 simulator. The simulation evaluates performance over an 85-year system inflow time-series (each year representing the year 2035) covering a range of hydrological conditions The performance information is passed back to ε-NSGAII for computing objectives and constraints upon which the algorithm evaluates the fitness of the decision variables and applies its operators to produce the next generation of decision variables. This represents one generation of the heuristic search process. The operator parameters such as the probability of crossover and mutation are user defined. Both of these operators when applied within real-coded genetic algorithms to multi-objective continuous problems have been proven to perform well (e.g. Deb and Kumar, 1995; Kollat and Reed, 2006). The parameter values for these operators were chosen based on recommendations of previous work that applied ε-NSGAII algorithm to a multi-objective problem (Kasprzyk et al., 2009; Kollat and Reed, 2006). The algorithm was run for 25,000 function evaluations based on a visual assessment of the convergence and time-varying diversity of the evolving solutions. The initial population size was set to 24 (equal to the number of cores used) and the algorithm operator parameters were chosen according to previous study recommendations (Kasprzyk et al., 2009; Kollat and Reed, 2007; Kollat et al., 2008). The algorithm parameters and objective epsilon values are summarised in Table 6.3. The epsilon values were set to capture the minimum level of precision to be used in distinguishing an alternative's performance in each objective. The population scaling factor directs the adaptive population sizing and represents the proportion of the population size at the beginning of new run which consists of the ε-archived individuals. For instance, the population scaling factor of 0.25 means that if there are 50 archived solutions at the end of one run, the following run will begin with the population size of 200, where one quarter will consist of the archived solutions and the remaining 150 individuals will be generated randomly. This improves the search by directing it with previously evolved solutions and by adding new solutions to further explore the search space (Kollat and Reed, 2006).

Random number generation can strongly impact evolutionary search, particularly the randomly generated initial search population. To minimise random seed effects the algorithm was run 50 times with different seed values. The results from each run are then sorted together to provide the best overall reference set based on the approach of Kollat et al (2008). It should be noted that this reference set was found to be nearly identical to the original run results which indicates the search solutions are replicable and likely highly representative of the true Pareto optimal set.

Table 6.3 Algorithm parameter and objective epsilon values used in the case study.

Algorithm parameters	Value	Objective	Epsilon
Initial population size	24	f_{cost}	500,000
Population scaling factor (for injection)	0.25	f_{rel}	0.05
Number of generations per run	250	f_{res}	0.10
Probability of crossover	1.0	$f_{minStor}$	1.00
Probability of mutation	0.5	f_{SI}	0.50
Distribution index for SBX crossover	15	f_{energy}	10,000
Distribution index for polynomial mutation	20	f_{SD}	0.10

6.5 Results

This section presents the results of the many-objective optimisation formulation discussed in Section 6.3 for the Thames planning problem. Figure 6.2 shows the approximation of the Pareto surface generated by the multi-criteria search process projected onto the two dimensional cost vs. LTCD level 3 reliability trade-off space. Each point represents a non-dominated solution, in this case, a portfolio of new supply and demand management measures. When the LAS storage drops below the LTCD level 3 threshold, hosepipe and non-essential use bans may be implemented by the water companies. Level 3 reliability is computed as the fraction of time-steps in the time horizon that were not below the LTCD level 3 failure thresholds. Many solutions display 100% reliability for the level 3 threshold. The left side of the figure is characterised by a steep cost to reliability gradient (i.e., small financial investments result in large reliability improvements). The cost vs. reliability subspace represents a classic lower dimensional view that has been the dominant focus of prior water resources systems design (Kjeldsen and Rosbjerg, 2004; Kundzewicz and Kindler, 1995; Lund and Israel, 1995; Rani and Moreira, 2009; Wurbs, 1993). This lower dimensional view shows the often discussed "flat surface" nature of the water supply cost and reliability performance measures yielding many solutions with seemingly identical levels of performance (Loucks et al., 1981; Loucks and van Beek, 2006). As was discussed in the introduction, this lower dimensional view can negatively bias decision making (i.e., cognitive myopia and hysteresis) hiding the broad array of water supply options that were discovered in the many-objective formulation.

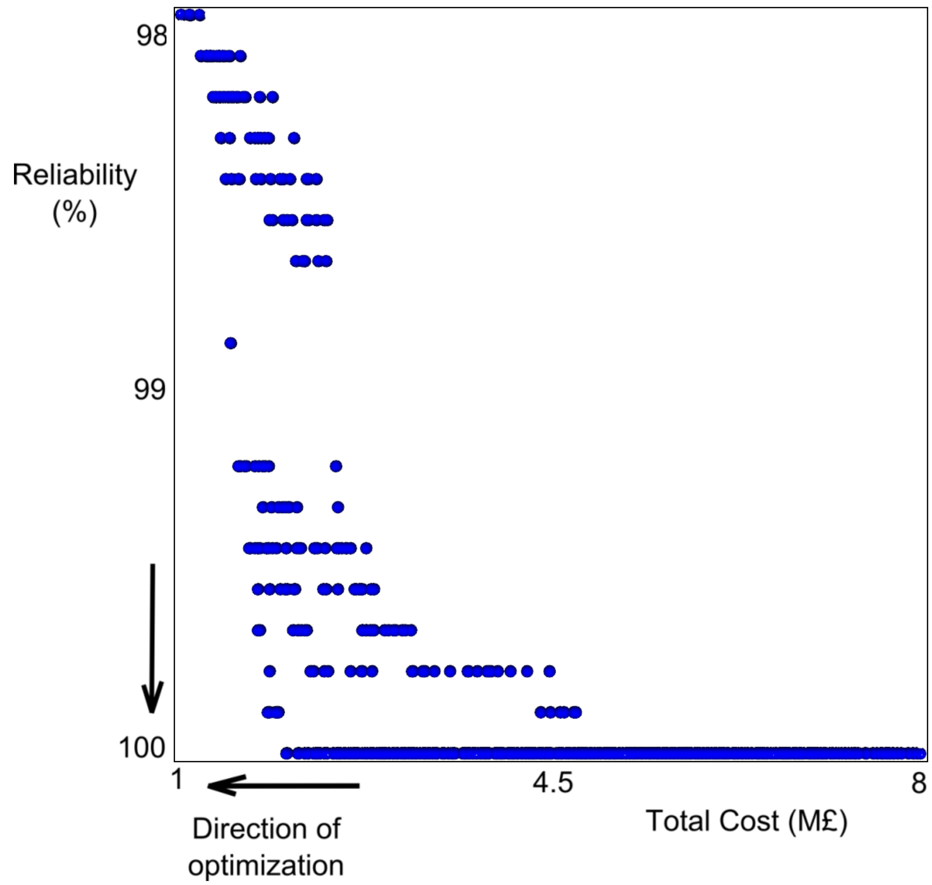

Figure 6.2 Two-dimensional plot showing the trade-off between Total Cost and LTCD reliability level 3. A steep trade-off exists cost and reliability, i.e. relatively low investments can achieve large increases in reliability. Many solutions have perfect reliability. The arrow points towards the optimization direction (optimal value of the objective).

Figure 6.3a and b show alternative views of the same Pareto optimal solution set. A key benefit of the many-objective visual analytics framework is that it facilitates rapid and interactive exploration of multiple views of the same high dimensional Pareto approximate set. These views strongly distinguish the performance of the solutions that appear as being analogous to one another in Figure 6.2. Figure 6.3a shows cost, ecological flow and reliability in the cardinal axes whilst cone size represents the energy requirements and cone orientation depicts the minimum reservoir storage metric. Figure 6.3b shows energy, resilience and the minimum reservoir storage dimensions in the cardinal axes whilst cone orientation shows the London supply reliability metric. These visualisations show the complex multi-dimensionality of the problem. Figure 6.3a shows that more expensive solutions have higher energy use and better performance in the engineering, reliability and environmental requirements but that the system can have relatively good ecological flow at a large range of costs.

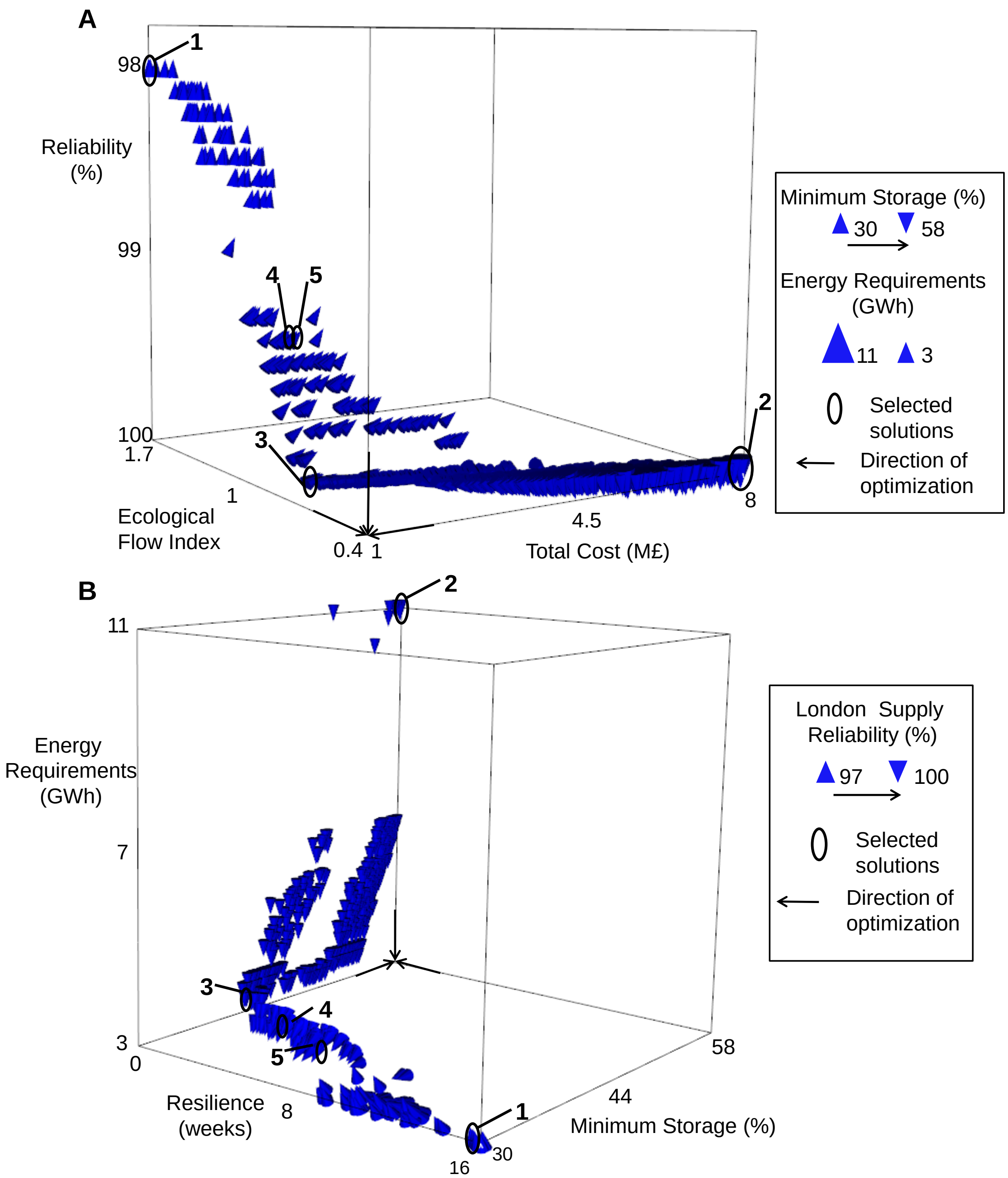

Figure 6.3 Many-dimensional plot showing the performance of the Pareto-optimal solutions. Plot A shows the reliability level 3, ecological flow and the cost performance metrics in the cardinal axes. Additionally the size of the cones and their orientations represent the minimum storage and energy metrics respectively. B shows energy, resilience and minimum storage in the cardinal axes whilst cone orientation shows London supply reliability. The arrows point towards the optimisation direction (optimal value of the objective).

Five solutions are singled out for further analysis in Figure 6.3. Solution 1, the ‘lowest cost’ solution, represents the lowest cost solution in the Pareto approximate set which satisfied the minimum service constraints (annual reliability Section 6.3.3.2). This option is the solution that a single objective least-cost subject to reliability constraints optimisation (i.e. EBSD, Appendix) would select. Solution 2, the ‘highest cost’ solution is Pareto optimal because of its excellent performance in all but the cost and energy performance measures. Solution 3 corresponds to the lowest cost solution that resulted in perfect level 3 reliability. Decision makers could pick solution 3, which is called the ‘cost efficient reliability’ solution if they were only concerned about reliability level 3 and cost. This ‘cost efficient reliability’ solution is an order of magnitude less costly than solution 2. The ‘lowest cost solution’ (1) has very similar energy requirements to the ‘cost efficient reliability’ (3) solution (Figure 6.3b) but has dramatically different resilience (Figure 6.3b) and reliability (Figure 6.3a). Solutions 4 and 5 show a compromise in performance in all objectives (compared to solutions 1, 2 and 3) except for energy use. In Figure 6.3b it can be seen that the minimum storage objective can increase from its minimum level of 30% storage (22.5% is a critical failure threshold, Section 6.3.3.2) to roughly 40% without much increase in energy. Solution 3 lies at a threshold between two distinct energy vs. minimum storage trade-off options. Both fronts result in increased energy use that provides gains in minimum storage, both paths have the best possible resilience (0 time-steps), but one front has better minimum storage than the other. These distinct fronts are the result of the discrete decision controlling of the activation of the Pipe refurbishment programme (shown in Figure 6.4). Figure 6.3a and b clearly demonstrate how changing which objectives are represented by the cardinal axes gives different insights into the geometrical relationships between metrics. In Figure 6.3a, the large solutions in lower right-hand corner containing solution 2 have similar performance in the reliability, cost and ecological flow objectives, but when viewed in Figure 6.3b these solutions can be differentiated further in the energy objective.

Figure 6.4 further explores the portfolio composition of the Pareto approximate solutions based on Figure 6.3b. The colours represent the activation of the mutually exclusive UTR or RST supply options; green represents solutions that include the UTR, red cones are portfolios that include the RST whilst blue cones are solutions that do not include either of these options. Opaque cones represent solutions that include the Pipe refurbishment programme in the London WRZ, a demand management option, whilst translucent cones are solutions that do not. Note that in the figure the intention is to show a mix of key decisions and a subset of performance objectives. As noted by

Tsoukias (2008), decision makers find the strict mathematical separation of decisions and objectives to be a false construct that can limit decision relevant insights.

By visualising decisions and objectives simultaneously Figure 6.4 allows decision makers to discover how different mixes (portfolios) of supply and demand options can quantitatively affect performance. For example, the inclusion of the RST scheme (red cones) results in an increase in energy requirements. Overall the opaque green cones form a steep front demonstrating that as the minimum storage objective improves more energy is required. The Pipe refurbishment decision also produces two groups of solutions with the inclusion of the option resulting in a capital cost increase in exchange for better performance in the resilience, reliability and minimum storage objectives. The red solutions include the RST and London pipes refurbishment (for all but one red solution). These infrastructure heavy solutions incur large capital and operating costs as well as increased energy requirements whilst attaining excellent resilience and reliability. To contrast, the blue solutions do not include neither of the UTR or RST options but have good energy performance and generally lower capital and operating costs. Solutions that include the UTR span a greater range of performance in all four objective dimensions and do not include extremes in performance, and can be described to have more ‘well-rounded’ performance. Furthermore these solutions include a variety of portfolios and have a wide range of cost performance as well as low to moderate energy use. Figure 6.4 clearly shows that the discrete water supply decisions yield distinctly different clusters of portfolio options (i.e. the groupings created by London Pipes, UTR, and RST). The figure further shows that although solutions 4 (‘Reservoir compromise’) and 5 (‘Pipes compromise’) exhibit similar performance, solution 4 includes the UTR and solution 5 does not include either the UTR or the RST. The ‘Pipes compromise’ solution is much less infrastructure intensive than the ‘Reservoir compromise’ solution but is able to achieve similar performance as solution 4 by refurbishing the pipes in London WRZ. Table 6.4 summarises the decisions and performance objective of the five selected solutions.

Table 6.4 Decisions and objective values characterised by the five selected solutions.Acronyms are defined in Table 6.3.

Solution	**1 (Lowest Cost)**	**2 (Highest Cost)**	**3 (Cost Efficient Reliability)**	**4 (Reservoir compromise)**	**5 (Pipes compromise)**
Objectives					
London Supply Reliability (%)	96.99	99.8	99.01	98.43	98.38
Total Cost (M£)	793428	8371290	1870490	2267180	2393990
Resilience (time-steps)	16	0	1	4.6	6
Reliability (%)	0.982	1	1	0.995	0.995
Ecological Flow Storage Index	1.65	0.38	0.95	1.08	1.09
Minimum Reservoir Storage (%)	29.79	57.55	40.03	37.3	35.83
Energy Requirements (GWh)	3396200	10729900	3773800	3595600	3375200
Supply decisions					
UTR Capacity (Mm3) /RST/NT	0	RST	149	77	0
SLARS Capacity (Ml/day)	0	23.2	0	0	0
DRS Capacity (Ml/day)	0	95.0	0	0	0
CT Capacity (Ml/day)	0	0	0	0	0
LRD	No	Yes	No	No	No
Demand management decisions					
London ALC (Ml/day)	0	49.5	0	32.3	0
London Pipes	No	Yes	No	No	Yes
London EFI	No	Yes	Yes	Yes	No
London Meters	Yes	Yes	Yes	Yes	Yes
Central ALC (Ml/day)	0	2.51	0	0	0
Central Pipes	No	Yes	No	Yes	No
Central EFI	No	Yes	Yes	No	Yes
Central Meters	No	Yes	No	Yes	No
Southern ALC (Ml/day)	0	2.03	0.37	1.61	0
Southern Pipes	No	Yes	Yes	No	No
Southern EFI	No	Yes	No	Yes	Yes
Southern Meters	Yes	Yes	Yes	Yes	Yes
Essex ALC (Ml/day)	0	1.19	0.84	0	0
Essex Pipes	No	Yes	No	Yes	No
Essex EFF	No	Yes	No	No	No
Essex Meters	No	Yes	Yes	No	No

The defining basis of visual analytics (Keim et al., 2010) is the exploitation of multiple, linked views of high dimensional data. The parallel axis plot (Inselberg, 2009) provides a highly scalable tool for exploring the trade-offs and performance differences of the five highlighted solutions illustrated in Figure 6.3a and b. The volumetric glyph plots discussed above show the strong geometrical context of the alternatives and when supplemented with the parallel axis plot in Figure 6.5 the full suite of the Thames system's trade-offs come into perspective.

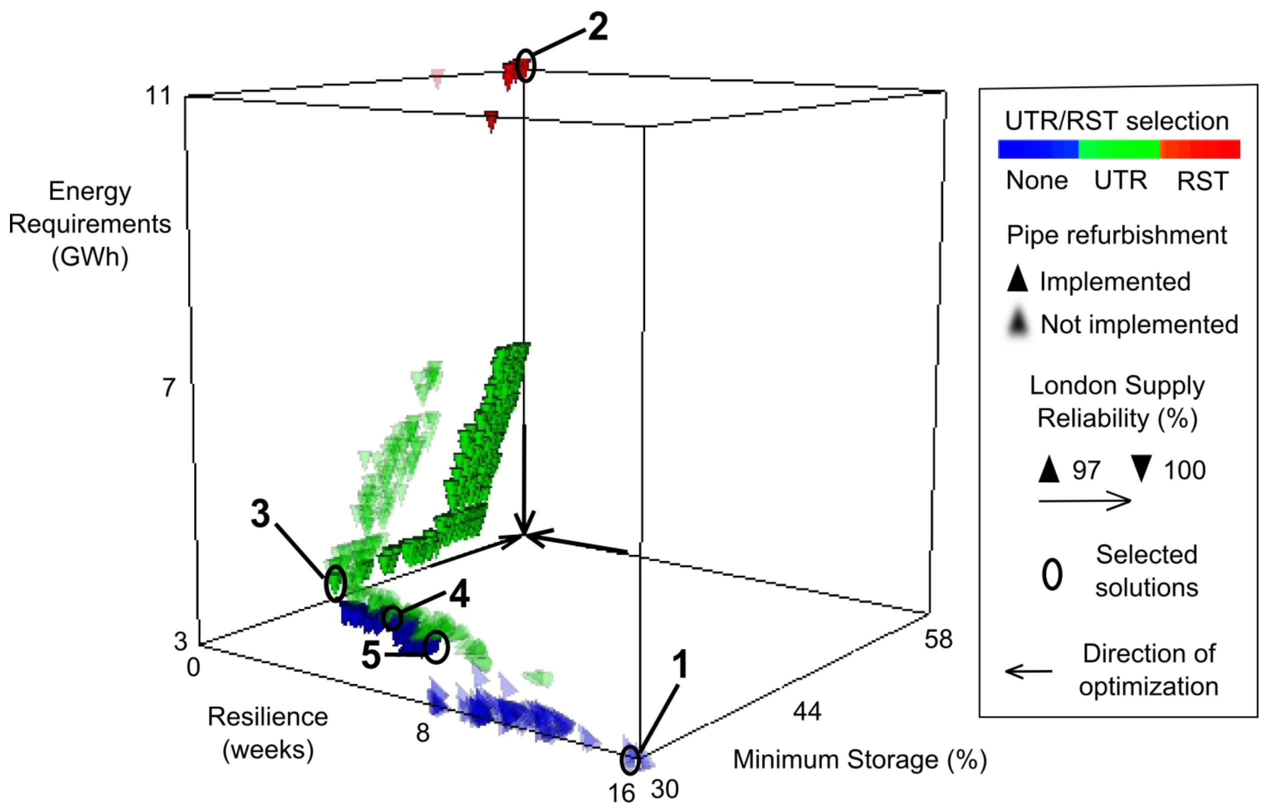

Figure 6.4 Many-dimensional plot showing groupings of different portfolio options and their performance. Each cone (glyph) on the plot represents a unique portfolio of supply and demand management measures. Opaque cones include solutions with Pipe refurbishment programme implemented, whilst translucent cones do not include the programme. Red solutions include the RST, green solutions include the UTR and blue do not include either. The orientation of the cones shows the reliability of portfolios. The arrows point towards the optimisation direction (optimal value of the objective).

By visualising decisions and objectives simultaneously Figure 6.4 allows decision makers to discover how different mixes (portfolios) of supply and demand options can quantitatively affect performance. For example, the inclusion of the RST scheme (red cones) results in an increase in energy requirements. Overall the opaque green cones form a steep front demonstrating that as the minimum storage objective improves more energy is required. The Pipe refurbishment decision also produces two groups of solutions with the inclusion of the option resulting in a capital cost increase in exchange for better performance in the resilience, reliability and minimum storage objectives. The red solutions include the RST and Pipe refurbishment (for all but one red solution). These infrastructure heavy solutions incur large capital and operating costs as well as increased energy requirements whilst attaining excellent resilience and reliability. To contrast, the blue solutions do not include neither of the UTR or RST options but have good energy performance and generally lower capital and operating costs. Solutions that include the UTR span a greater range of performance in all four objective dimensions and do not include extremes in performance, and can be described to have more 'well-rounded' performance. Furthermore these solutions include a variety of portfolios and have a wide range of cost performance as well as low to moderate energy use. Figure 6.4 clearly shows that the discrete water supply decisions yield distinctly different clusters of portfolio options (i.e. the groupings created by London mains, UTR, and RST). The figure further shows that although solutions 4 ('Reservoir compromise') and 5 ('Pipes compromise') exhibit similar performance, solution 4 includes the UTR and solution 5 does not include either the UTR or the RST. The 'Pipes compromise' solution is much less infrastructure intensive than the 'Reservoir compromise' solution but is able to achieve similar performance as solution 4 by refurbishing the pipes in London WRZ.

The defining basis of visual analytics (Waage and Kaatz, 2011) is the exploitation of multiple, linked views of high dimensional data. The parallel axis plot (Jinno et al., 1995) provides a highly scalable tool for exploring the trade-offs and performance differences of the five highlighted solutions illustrated in Figure 6.3a and b. The volumetric glyph plots discussed above show the strong geometrical context of the alternatives and when supplemented with the parallel axis plot in Figure 6.5 the full suite of the Thames system's trade-offs come into perspective.

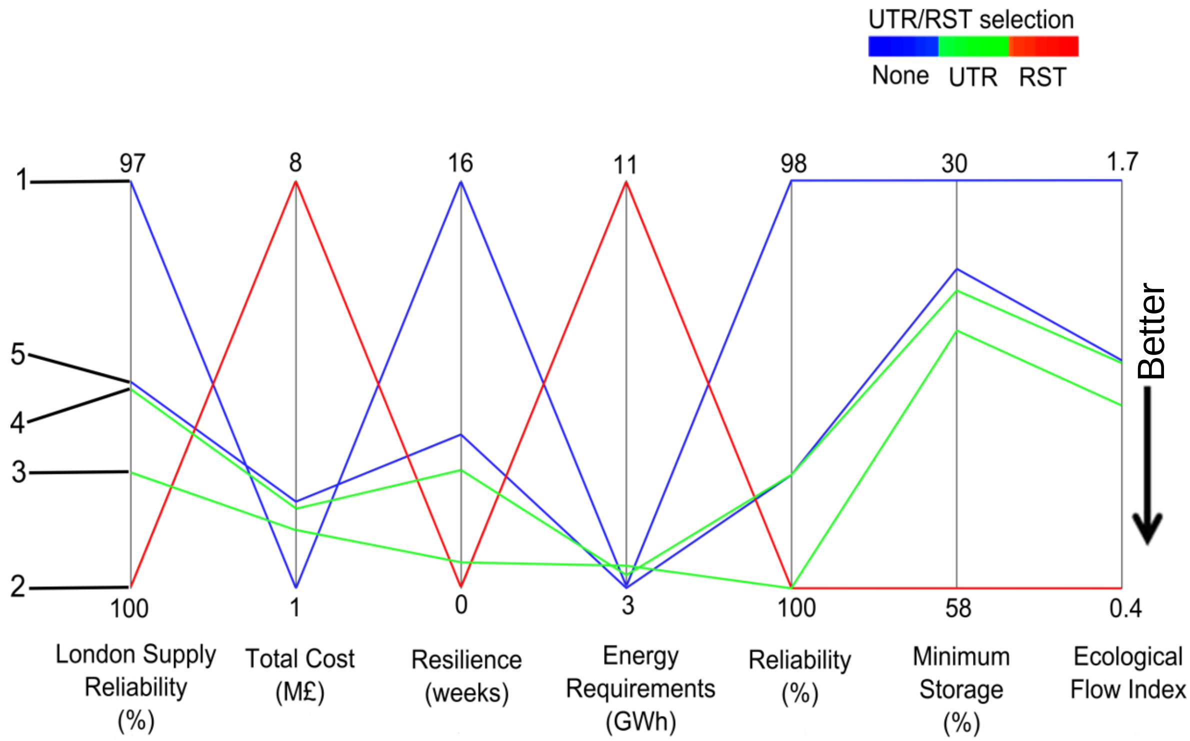

Figure 6.5 Parallel plot of the five selected solutions. Each line on the figure represents the performance of one candidate Pareto approximate solution. The intersections of the lines with the vertical axes represents the objective performance. The arrow points towards the optimisation direction (optimal value of the objective). Ideal performance would be a horizontal line at the bottom of the axes. Diagonal lines represent objective trade-offs.

The parallel axes plot shown in Figure 6.5 captures the trade-offs between the full suite of Thames water supply objectives. When interpreting Figure 6.5 each vertical axis represents objective performance. Each line represents the many-objective performance of the five highlighted solutions. An ideal solution would be a horizontal line intersecting the bottom of every axis. Conflicts in the objectives are represented by diagonal lines between the respective objectives' vertical axes. Trade-offs exist between London supply reliability, cost, resilience, energy loss and level 3 reliability and minimum storage. Solutions 1 and 5 perform very well in the energy metric, but have reduced performance with respect to the reliability objective. Solution 2 has strong performance in reliability but not energy. Similar relationships can be seen between other pairings. This helps decision makers visualise the consequences of only considering one or two objectives. As depicted in Figure 6.3 solutions 1 and 3 have 100% reliability. However, the parallel plot demonstrates that these solutions exhibit significantly different performance in each of the other performance metrics.

All solutions except for solution 2 perform well in the energy objective whilst solution 3 has good performance in most of the objectives. Despite the major infrastructure differences between solutions 4 and 5 (solution 4 includes the UTR whilst 5 does not) they have similar performance in all metrics. Neither of these solutions include any other supply options demonstrating that, as modelled, demand management measures produce similar system performance as a small scale UTR (75 Mm^3). The least infrastructure intensive portfolio, solution 1, displays the worst performance in the London supply reliability, resilience, reliability, minimum storage and ecological flow metrics but has the best performance in the cost and energy measures. Conversely, the most infrastructure-intensive portfolio, solution 2, exhibits the best performance in all but the cost and energy metrics. In these two metrics it performs better than all the other solutions.

Many-objective visual analytics gives information that would be missed using single-objective optimisation. Visual analytic plots enable planners to 'browse' the Pareto front and introduce preferences for individual options based on non-optimised factors (ease of construction, land use, public opinion etc.). For example Figure 6.4 shows that a portfolio with UTR (solution 4 in the figures) and another without UTR (solution 5 in the figures) exhibit similar performance in the ecological flow metric, cost and reliability metrics, the energy requirements and minimum storage (Figure 6.6). Identifying these options on Figure 6.3 shows this is achieved by activating London pipes refurbishment instead of the UTR. The replacement of leaking water pipes vs. adding a new reservoir needs to be decided by strategic thinking on how these options help meet other less tangible goals (e.g., the relationship with regulators and client base).

The volumetric glyph and parallel axis plots show the performance objectives of each solution evaluated over the whole of a simulation run. The use of a simulation model in this optimisation approach allows for direct performance comparison between any of the Pareto-approximate plans at any time-step. Figure 6.6 shows the simulated results for the London aggregate storage node during a major drought for each of the five selected portfolios. The plot serves as a reminder that each cone or point in the Pareto optimal plots is backed up by a detailed and realistic system simulation. The London Aggregate Storage (LAS) node remains at 100% capacity during the drought for the 'Highest cost' portfolio (solution 2) because this plan has high redundancy. Choosing this portfolio may result in over-investment in infrastructure. Figure 6.4 and Figure 6.5 show that despite its good performance in the environmental and engineering metrics this portfolio is the most expensive and energy intensive one found in the Pareto approximate solution space. The ‘Lowest cost’ solution 1 performs most poorly. Out of all the possible supply and demand management options, solution 1 only includes London and Southern meters. In this early 1930s drought scenario, the existing storage becomes stressed signalling that solution 1 may suffer from under-investment. In the 1920’s drought (not shown) the minimum storage for solution 1 goes down to 30% storage, which is very near the 22.5% critical threshold. Solutions 3, 4 and 5 have similar minimum storage performance. Solution 3 includes a large capacity UTR but includes fewer demand management options. Solution 4 includes a small capacity UTR and a different mix of demand management options (notably the inclusion of London ALC in solution 3). Solution 5 does not include the UTR but includes London mains. Solutions 3, 4, 5 are good candidates for droughts such as the one seen in Figure 6.6.

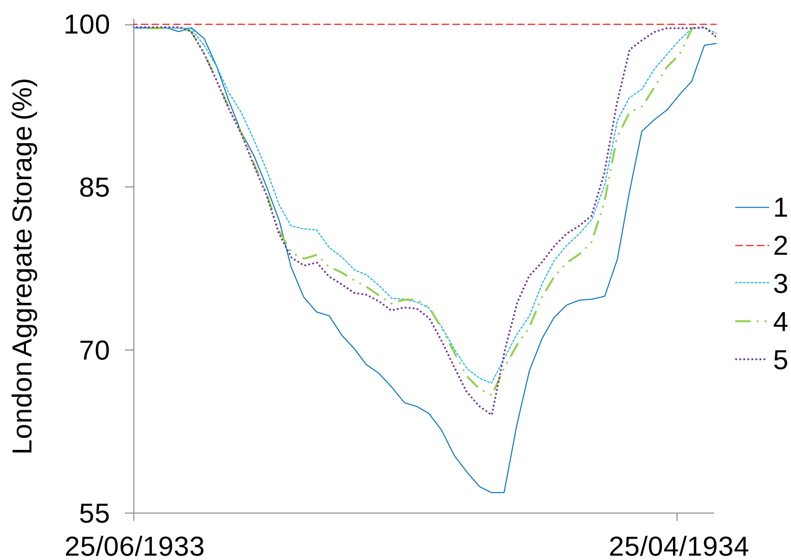

Figure 6.6 Minimum storage performance of the five selected solutions during a major drought event.

6.6 Discussion

In this study a water system simulator was linked to a multi-criteria search algorithm to generate a diverse set of Pareto-optimal water supply portfolios. The set was assessed using visual analytic plots that reveal the trade-offs in performance space and that map the composition of portfolios to the trade-offs. Below the innovations, limitations and implications of the water planning approach presented here are discussed.

6.6.1 Increasing plan quality by increasing problem dimensions

Increasing the number of dimensions considered in scheme selection gives decision makers information they would not have if the problem were solved considering fewer factors of performance. In this example the 'lowest cost' (selection 1) solution meets minimum service reliability requirements imposed by regulators (Section 4.3). Had decision makers only considered cost they would have likely chosen this portfolio. The parallel plot (Figure 6.5) reveals this portfolio (solution 1) performs poorly in the London supply reliability, resilience, reliability, minimum storage and ecological flow metrics. Similarly, if reliability were the sole selection criteria (with perhaps a maximum cost constraint), single objective optimisation would lead to multiple optima as many solutions in the Pareto front display perfect reliability (Figure 6.2). Of all the solutions with 100% reliability, all are non-dominated and have a range of varying performance in other objectives. Without the possibility to visualise these other dimensions, valuable gains could be missed and even the presence of multiple optima along one metric could be easily missed. Considering multiple objectives allows these solutions to be differentiated (Figure 6.3). Figure 6.3a and b show how solutions can have similar performance in some metrics but have diverging performance when seen using other dimensions (panel b).

Recent work by Woodruff et al. (2013) corroborates the findings and suggests how aggregated analyses of complex engineered systems can suffer from myopia and mathematical biases that lead to opportunity costs by ignoring key trade-off alternatives between otherwise aggregated metrics. These aggregations occur for example in traditional cost minimisation-only approaches (Padula et al., 2013) and cost-benefit analysis (Banzhaf, 2009).

6.6.2 Visualisation

Many-objective visual analytics allows decision makers to survey the trade-offs between objectives and to distinguish the effects of individual supply or demand options within the Pareto approximate set (Lotov and Miettinen, 2008). Visualisation of trade-offs in multiple dimensions is well suited for situations where stakeholders have diverse interests. For instance, an environmental regulator could be interested in how different portfolios impact the environmental flows downstream of abstraction sites whilst water companies could be interested in seeing how well portfolios meet service reliability requirements.

It was demonstrated that it is important to exploit visual analytics to promote linked views of both performance objectives and investment decision variables simultaneously. It was shown how the

Thames system's Pareto approximate portfolios 'cluster' into distinct suites of water supply options. Visualising these diverse groups of water supply plans in performance space provides water managers with a rich perspective on key decision trade-offs and significant flexibility when choosing alternatives for further consideration. The many-dimensional visualisation allows decision makers to consider the quantifiable performance metrics and navigate through them directed by further considerations not considered in the optimisation (such as easiness of construction permits, land rights, etc.). Decision makers can quickly build a mental map of the consequences of including certain water supply schemes.

6.6.3 Using the proposed approach in water planning

The multi-criteria planning approach proposed here is more complex to implement in a regulated industry (as exists in England) than the current least-cost approach because the relevant performance metrics and relevant stakeholders vary somewhat by region and system. For each application a concerted effort would need to be made to define the most regionally relevant system goals, iteratively working with stakeholders to develop appropriate performance measures. A stakeholder-driven planning approach using the proposed methods would benefit from stakeholders a) defining system goals (metrics) to be optimised, b) interactively using trade-off visualisations and c) interacting in a deliberative forum to negotiate down to one or to a reduced number of preferred plans. Task b) could for example include stakeholders adding *a posteriori* minimal acceptable performance thresholds and "brushing" (Kasprzyk et al., 2013) out solutions (erasing them from trade-off plots) that do not meet these negotiated preferences from task c), thus reducing the number of solutions to consider. Stakeholder use of Pareto-optimal trade-off analysis for collaborative decision-making and negotiation will benefit from further research.

6.6.4 Limitations

A limitation of the application described here is its consideration of one set of future conditions: it assumes historical inflows are representative of future plausible ones and that future demands are known. The historical record used in this study contains several severe droughts and therefore provides a useful stress test for future system designs. A 30-year historical hydrological record is used in the current planning framework English water companies use, substantially shorter than the ones used in this study. This deterministic study provides a baseline against which results from a future stochastic or multi-scenario implementation could be compared. An implementation accommodating multiple plausible futures could incorporate the uncertainty of exogenous and endogenous factors into the planning approach.

The MOEA application was able to consider many more options, including their different capacities and combinations, than both the RDM and Info-gap approaches. However, one limitation as compared to EBSD is that this application did not perform options scheduling (optimising the for the build year of each option). Incorporation of options scheduling increases the number of decision variables and makes the problem significantly more computationally expensive. Scheduling was beyond the scope of this study and is left for future work.

6.7 Conclusions

Water resource system and water supply planning are inherently multi-objective problems where decision makers must balance complex priorities such as costs, reliability, ecosystem services, etc. Single-objective planning such as least cost optimisation gives planners only part of the picture when planning real systems where many aspects of system performance are relevant. Even if all system goals can and have been translated to one commensurate unit system (typically monetary), planners would lack the ability to understand the trade-offs embodied by different plans. This study presented a water supply planning optimisation model with 7 simultaneous objectives: minimise costs and energy use whilst maximising environmental performance and engineering performance metrics such as resilience and reliability. The objectives were subject to regulatory supply reliability and environmental flow constraints. The optimisation problem was solved by linking a water resource system management simulation model and a many-objective evolutionary optimisation algorithm. The multi-criteria search engine used the system simulator as the optimisation function evaluator.

The approach was applied to identify promising designs for London's future water supply system for the year 2035. Seven supply and four demand management options with a range of possible capacities were considered in a capacity expansion optimisation formulation considering seven engineering and environmental objectives. The output of the optimisation was a set of approximately Pareto-optimal (non-dominated) portfolios of supply and demand management schemes. Results showed that, given the set of new options tested in this study (from the 2009 price review), the Upper Thames Reservoir (UTR) combined with demand management options creates a reliable system at a relatively small incremental cost. It was also shown that a demand management-intensive portfolio performed similarly to a plan that included the new UTR reservoir. Visualising time-series of detailed simulated results that underlie each point ('glyph') on the trade-off plots helps planners assess system responses to specific extreme events and helps prevent over- and under-investment.

State-of-the art many-objective visual analytics was used to explore the Pareto optimal solution space which manifests as a multi-dimensional trade-off surface. These multi-dimensional visual aids help analysts and decision makers see how individual supply and demand management options affect performance in each dimension. Portfolios which share certain schemes were seen in some cases to cluster in some parts of the decision space showing that choosing certain options leads to certain types of performance. Conversely, other parts of the Pareto front revealed that quite different portfolios had similar performance. Together the graphics underline the complexity of planning when many metrics of performance are relevant and the richness of information achievable through a multi-criteria search-based approach. The visual analytics graphics allow decision makers to assess trade-offs between objectives and how different options and portfolios of options map to those trade-offs. The study showed that in cases where multiple optima are present in one dimension, other objectives can be used to differentiate between these solutions.

7 Conclusion and future work

7.1 Summary

Uncertainty in future conditions and changing stakeholder priorities are imposing a rethink of the current methods employed by decision makers to develop water resource system plans. Current planning methods (such as EBSD) often employ classical optimisation algorithms such as mathematical programming. These methods have known success but have several key limitations: 1. they typically require simplified spatially and temporally aggregated system models that have difficulties representing non-linearities; 2. if multi-objective they are unable to perform the weighting or prioritisation of objectives *a posteriori* 3. they grapple with cases where planning is performed under conditions of ‘deep’ uncertainty in future conditions.

The overarching aim of this thesis was to investigate planning methods that take into account the ‘deep’ uncertainty of future conditions and explicitly consider different stakeholder interests. To accomplish this goal the first objective was to develop a detailed and computationally efficient water resource system simulation simulator that could quantify performance system in multiple performance metrics. This contribution is introduced in Chapter 3. As part of this thesis the IRAS-2010 software was developed from its original state making it suitable for modern water systems planning. The new code includes new features, making it flexible and able to simulate complex surface and groundwater systems. The code is computationally efficient and has been made open-source. Using IRAS-2010 the Thames basin water resource system was modelled. This model has been shown to successfully emulate a commercial model (AQUATOR) maintained by the Environment Agency of England and Wales. Modified versions of this model were used in the planning studies described in the subsequent chapters of this thesis.

The second objective of this thesis was to investigate two state-of-art decision making frameworks (Robust Decision Making and Info-Gap Decision Theory) that could aid planners in finding plans that are robust to the ‘deep’ uncertainty of future conditions. Robust solutions are those that perform well over a wide range of future conditions. Chapter 4 contributed two Robust Decision Making (RDM) framework studies on the real-world Thames basin planning problem: one that considers new supply options (a new reservoir, water transfer, conjunctive use groundwater scheme and running a desalination plant at two capacities) and one that includes supply and demand management options (metering, seasonal tariffs, leakage reduction and efficiency improvements). Both studies seek portfolios that are robust to 'deep' uncertainty in future hydrology, demand and energy prices. Following the RDM framework possible Thames water resource system strategies were simulated under a wide range of possible future conditions (15,400 and 3,850 possible future scenarios were simulated in the supply-side and supply and demand management option RDM studies respectively) composed of climate change perturbed hydrologies, demand levels and energy prices. Engineering, environmental and cost performance was considered. Using regret analysis the strategy that was the most robust to these future uncertainties was identified. In the final step the scenarios under which the most robust strategy is likely fail to fail to meet minimum performance criteria were identified.

Chapter 5 of this thesis contributed a comparison of the RDM framework to Info-Gap Decision Theory. The problem formulation was similar to that of the supply-side only RDM implementation and included the same portfolios and uncertainty dimensions. Like RDM, an Info-gap analysis requires the simulation of potential water resource system portfolios under a wide range of possible conditions. Info-gap characterises uncertainty as a set of nested sets centred around the best estimate of each uncertainty dimension. In practice this involves simulating each portfolio under conditions defined by the best estimates of each uncertainty dimension and progressively simulating more dire and favourable conditions in each dimension. Info-gap defines the robustness of each portfolio as the maximum deviations ('horizons of uncertainty') from the best-estimate each portfolio can tolerate before failing to meet minimum performance requirements. Info-gap recommended a similar (but not identical) portfolio as RDM.

The third objective of this thesis was to investigate a method that linked the IRAS-2010 simulation model to a multi-objective evolutionary optimisation (MOEO) algorithm and search through the many proposed system infrastructure and demand management expansion options to produce the best plans that make up multi-dimensional Pareto trade-off surfaces. Trade-off surfaces allow stakeholders to visualise the inherent trade-offs between performance metrics. This contribution was presented in the last chapter of this thesis. The multi-objective evolutionary algorithm found plans that minimise costs and energy whilst maximising engineering and environmental performance. Multi-objective visual analytics was used to explore the Pareto-approximate surface.

7.2 Conclusions and observations

7.2.1 Robust Decision Making and Info-Gap Decision Theory

The RDM and Info-gap methods are multi-criteria scenario-based simulation methods. Their main advantage is that they favour robustness rather than optimality in the face of 'deep' uncertainty. These approaches allow greater detail and rigorous treatment of uncertainty, but they are not able to assess the same number of options and combinations thereof as the economic optimisation approach. A few options with ranges of possible capacities (even if coarsely discretised) quickly lead to a unmanageable number of possible scheme portfolios; it can appear arbitrary to select only a few of the many possible alternatives to simulate and assess. Increasing the number of options or uncertainty dimensions renders the problem so computationally burdensome that it is impossible to solve within a realistic time-scale with resources available to most water system planners. When using these methods, planners must choose *a priori* a small number of portfolios to consider. For this reason RDM and Info-gap are better suited for a possible intermediate step within the planning process. These methods could be used after planners have narrowed down the number of options to consider (through other decision making frameworks) and want to choose amongst them, improve the plans' robustness or to give decision relevant information. Using 'scenario discovery' RDM provides decision relevant information by quantifying the vulnerable realm of the candidate strategy whilst, through robustness curves, Info-gap can be used to tell the decision maker in which performance metric each portfolio failed. This decision relevant information can be used to consider plan ameliorations and improve robustness.

7.2.2 Combined many-objective evolutionary optimisation and simulation

The multi-objective evolutionary optimisation approach frees planners from having to choose *a priori* which portfolios of options and at which capacities to consider; instead the search for the best groupings of options and their capacities is automated as in the current planning method, EBSD. This method, however, is able to consider multiple performance dimensions and can prevent the decision bias that may occur when optimisation is performed with fewer dimensions. If detailed trusted simulators are used in the proposed analysis, and performance metrics used in the optimisation have been defined with stakeholders, the Pareto-optimal solutions such as those presented in Chapter 6 will likely be of interest to decision makers. Such visualisations give decision makers a rich perspective and insights on the many possible portfolios and how they perform in each objective. A limitation of the approach as implemented here is that it is deterministic and did not seek robustness. The optimisation was performed considering only one future demand scenario and the simulation model was run using only historical hydrology. Research currently in progress not described in this thesis involves a stochastic application that introduces uncertainty into this optimisation problem. Implementing the search with principles of robust optimisation could provide a degree of robustness to the solutions presented on the Pareto surface.

7.3 Limitations and future research

7.3.1 Limitations of the case-study

This thesis focused on investigating state-of-the-art planning methods with an emphasis on the UK context. These methods were applied to a single case-study: the Thames basin water resource system planning problem. Therefore, the observations, benefits and limitations of the methods derived from the studies in this thesis are based on a single case-study. Other water resource planning problems may reveal other observations not found in this study.

Furthermore, certain assumptions and simplifications were made that - whilst appropriate for the scope of this thesis - may underrepresent the complexity and diversity of water resource systems. One of these simplifications is found in the choice of performance metrics. For example, the environmental shortage index used in these studies was particularly simplified and did not rigorously take into account how the new options affected the flow regime in the Thames. In more complex studies using these methods, stakeholders and regulators may use more complex performance metrics. Other case-studies may also require specific performance metrics not discussed here (e.g. hydropower performance, flood alteration, irrigation, etc…).

The climate scenarios used throughout this thesis may also underrepresent the true complexity of the potential effects of climate change on hydrology. Using flow factors to perturb historical hydrology is accepted practice in England and Wales as defined in the Environment Agency's 'Water Resources Planning Guidelines' (EA, 2011). However, this method does have its limitations. In an application that uses precipitation and temperature change factors Prudhomme et al. (2010) describe some of the limitations of the change factor method stating that it yields uniform changes to all events and that it leaves the frequency of extreme events unchanged. In this context, all droughts and wet periods irrespective of their magnitudes are perturbed by the same factor and they occur at the same frequency that is found in the historical series.

7.3.2 Options scheduling

In addition to selecting which supply and demand options to implement and at which capacity, the EBSD framework provides their sequence of implementation i.e. when to implement each option. Including options scheduling in company water resource management plans is a requirement imposed by regulators (Environment Agency, 2012). Option sequencing is often performed together with capacity expansion (called the scheduling capacity expansion problem (Mortazavi-Naeini et al., 2014) using classical methods like linear programming (Appendix) and dynamic programming (Knudsen and Rosbjerg, 1977) often by minimising the net present cost of the plan.

As scheduling is a requirement imposed by regulators, it should be incorporated in any new revamped water resource system planning framework in England and Wales. The case study in this thesis only considered static conditions (i.e. conditions in the year 2035) and as such the RDM, Info-gap and MOEO methods described in this thesis did not address options sequencing. Scheduling requires dynamic conditions where input data changes overtime (e.g. demand growth or yields of built options).

7.3.3 Future research

One option to include scheduling is to use one or more of the methods described in this thesis (according to the recommendations above) to develop a static water resources plan and then to perform an options sequencing analysis in order to find the optimal sequence of options using classical methods. However, because of the same limitations described for the capacity expansion problem without scheduling (as described by the research problem, Section 1.6) this would preclude a detailed multi-objective analysis and would not consider 'deep' uncertainty, the two main limitations of current planning methods that are addressed in this thesis.

One potential method to incorporate options scheduling is to implement real-options in the planning framework. Real-options is a method that helps decision makers identify strategies that cope with uncertainty by incorporating adaptation and flexibility into their design. Real options in projects (Wang and de Neufville, 2005) involves changing the actual design of a technical system to incorporate flexibility and adaptation. In general uncertainty is greater for time further in the future. A system built with the principle of real options gives managers the flexibility to amend the system as information about the future becomes known. Woodward et al. (2013) show that flexible systems result in higher benefits for the same costs. Adaptive options, including real-options and decision tree analysis, could be integrated into the Thames basin case-study multi-objective optimisation. The planning horizon would be split into planning stages. Each possible supply and demand management option would have an implementation threshold which would be based on a low-flow metric (e.g. average summer flow in the Thames below a certain level for 5 consecutive years) and/or high-demand trigger. These triggers would be included as decision variables in the optimisation in addition to the capacity of the option. Following Basupi and Kapelan (2014) this implementation would be done stochastically where multiple demand time-series would be constructed sampling a demand probability distribution at each planning stage (or possible every year). An ensemble of equi-probable dynamic flow time series would be used for climate uncertainty. These dynamic flow time-series would be incorporated for supply infrastructure such as the Upper Thames Reservoir or new desalination plants where the initial options could be expanded further into the time horizon. These approaches and their implementation are left to future work.

8 Appendix - Solving the Thames basin planning problem with EBSD

This appendix details a supply and demand management option planning problem for the Thames basin (Padula et al., 2013) that was solved using Economics for Supply and Demand, the current water resource system planning framework used by water companies and regulators in England and Wales. This planning problem is similar to the one presented in Section 4.4.

8.1.1 Regulatory context and model formulation

The water resource management guidelines (Environment Agency, 2008a) require water companies to forecast demand under dry year annual average (DYAA) and dry year critical period (DYCP) conditions assuming no demand restrictions.

The EBSD framework typically uses a mixed integer linear programming (MILP) network model composed of supply and demand nodes connected by links. Demand nodes represent WRZs whilst supply nodes represent available existing and optional supply and demand management schemes (Padula S. et al., 2010). Links can also represent transfers between WRZs (Figure 8.1). This forms a quasi-spatial network where supply options can have real associated geographical locations but for data management are usually organised in 'rings' around the demand nodes as seen in Figure 8.1.

The objective function is the sum of discounted capital and operating costs (fixed and variable) of new options and bulk transfers as well as estimated environmental and social costs incurred by the new options. Both the DYAA and DYCP supply-demand problems are solved in a single model concurrently in order to guarantee that the proposed plan meets both demand levels in each year.

One integer set of variables represents the selection of new supply and demand options whilst two sets of continuous decision variables (one each for the DYAA and DYCP scenarios) describe how much each scheme is used each year. One set of capital (CAPEX) and fixed operating (FOPEX) is used. The two demand scenarios have differing variable operating (VOPEX) costs and so a weighted average of VOPEX costs is included in the objective function formulation considering 42 weeks/year duration for the DYAA scenario and 10 weeks/year duration for the DYCP scenario. The DYCP scenario is only considered when WRZs are determined to be sensitive to peak demands.

The formulation constraints include non-negativity of decision variables, mass balances, limitation on capacities and start date constraints to limit the first use of optional schemes. Possible interdependencies between the nodes and/or links in the network are also considered including exclusivity, dependency and prerequisite constraints.

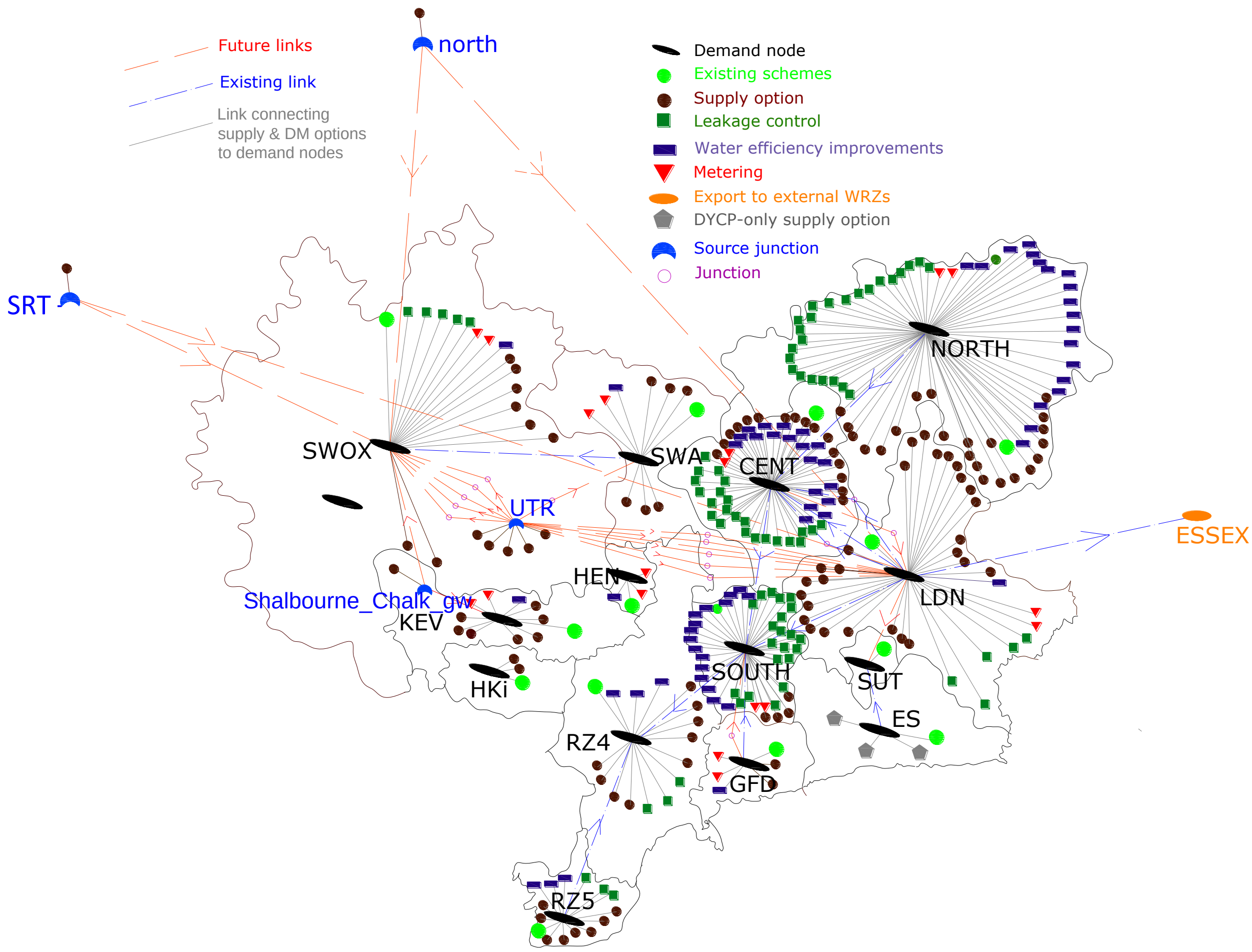

Figure 8.1 Modelled Thames catchment water resource system links between WRZs represent transfers; links between options and demand nodes within a WRZ are a mathematical artifice of the network model formulation (not representing actual conveyance).

8.1.2 Water resource system – demands and existing and proposed options

A mixed integer linear programming (MILP) optimisation model (Padula et al., 2013) is used to determine the least discounted cost supply and demand management portfolio for a supply-demand network that represents a regional system of twelve WRZs included inside River Thames catchment. Five water companies (WCs) manage the water resources within these zones: Thames Water Utilities Limited (TWUL), Southeast Water, Southern Water (SW), Sutton & East Surrey Water and Veolia Three Valleys Water (VTVW). The input data (demands by WRZ, costs and capacities of existing and optional schemes) used in the model originate from the 2009 draft Water Resource Management Plans (WRMP) water companies submitted to regulators during the most recent 5-year 'price review' (Essex and Suffolk Water, 2010; Sutton & East Surrey Water, 2009; Thames Water, 2010; Veolia Water Central Limited, 2010).

The water resource system is represented by a node-link network. Links represent rivers, pipelines or canals. These links are either existing (continuous lines and dash lines with dots in Figure 8.1) or future options (dash lines). Nodes represent demand areas, supply sources, demand management options or junctions. Supply/demand management nodes can be either existing (light circles) or optional (dark circles). Losses, target headroom (the buffer between supply and demand) and water demands are aggregated on the WRZ level. The light ellipse nodes represent export of water to WRZs outside the Thames basin. Future demands are specified for each WRZ level (Figure 8.1).

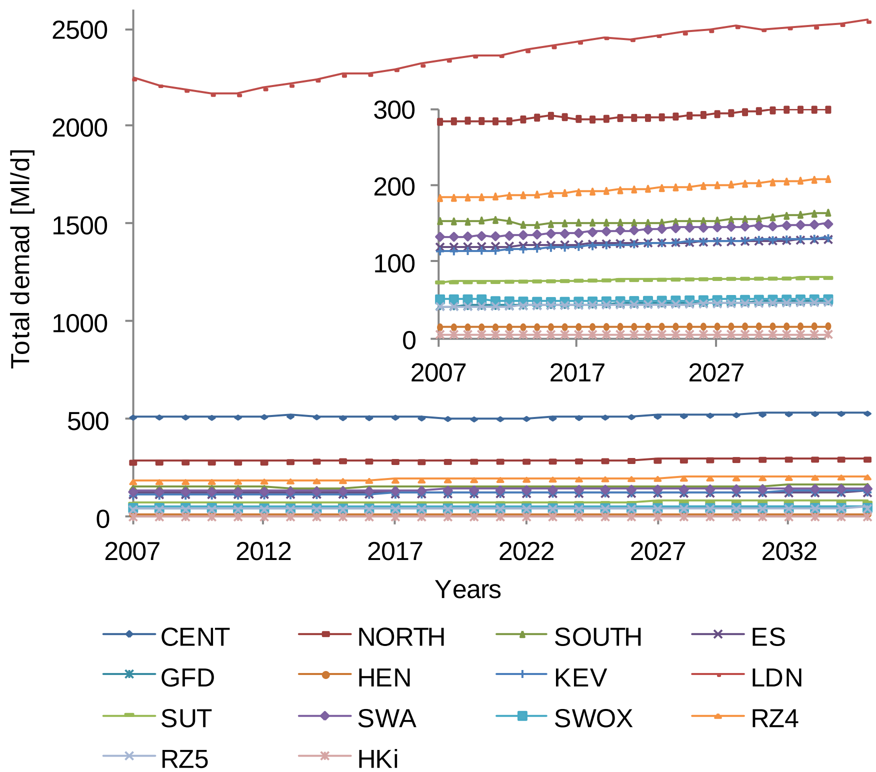

Figure 8.2 Estimated total annual demand (distribution input plus target headroom) over the planning horizon for each water resource zone ('WRZ') included in the Thames catchment area. The highest demand and biggest deficit occurs in the London (LDN) WRZ.

Supply nodes represent reservoirs, groundwater or surface water abstraction, effluent reuse schemes, desalination, aquifer storage and recovery, intra-company transfers or transfers between water companies. The major schemes considered in this study are briefly described. Four implementations of the proposed Upper Thames Reservoir (UTR) are considered. These are 75 Mm^3 (RA75), 150 Mm^3 (RA150 and RA3Z depending on which WRZs are served) or a 150 Mm^3 reservoir built in a two stage process (RAP1 and RAP2 at 75 Mm^3 and 75 Mm^3) (Thames Water, 2009). Other major schemes include: the Severn river Transfer (links SRT-LND, SRT-SWOX), the Northern England Transfer and the South London Artificial Recharge Schemes (SLAR_south, SLAR_kidbrooke) (Thames Water, 2009).

Demand management schemes are divided into three categories: metering (MET), leakage reduction (LR) and water efficiency measures (WEF). LR options include: mains renewal or replacement, pressure management, increase of speed of repair, new detection technologies, district metering, and global supply pipes. Pro-actively fixing leaks before they're reported is referred to as active leakage control (ALC). For ALC planning water companies consider 'tranches' (bundles) of ALC implementation; each tranche is represented in the model as a different option. As a prerequisite each successive tranche must have its previous tranches activated (option 'active leakage 2' can only be activated after 'active leakage 1', etc.). Successive leakage control activities result in diminishing returns: WAFU is the same for each tranche but capital and operating costs increase substantially. Metering (MET) options include targeted compulsory metering and change of occupancy metering (COM). Water efficiency (WEF) options include household and commercial customer audit programmes and water efficiency awareness campaigns. WEF options also include tariff options (Three Valleys, 2008): 'Rising Block Tariffs' and 'Summer Winter Tariffs'.

8.1.3 Results and discussion

The least-cost infrastructure planning model for the Thames system was solved simultaneously for the DYAA and DYCP demand scenarios. The model output includes a 29-year optimal programme of scheme implementation which is shown as a time-series (Figure 8.3) or in plan view in Figure 4.9. Please note these recommendations are based on limited publically available data found in water companies' draft WRMPs. In addition to scheme selection and scheduling, results also include the optimal annual quantity of water supplied by each source and link to meet WRZ DYAA and DYCP water demands. Figure 8.3 shows this as a time series for the DYAA scenario.

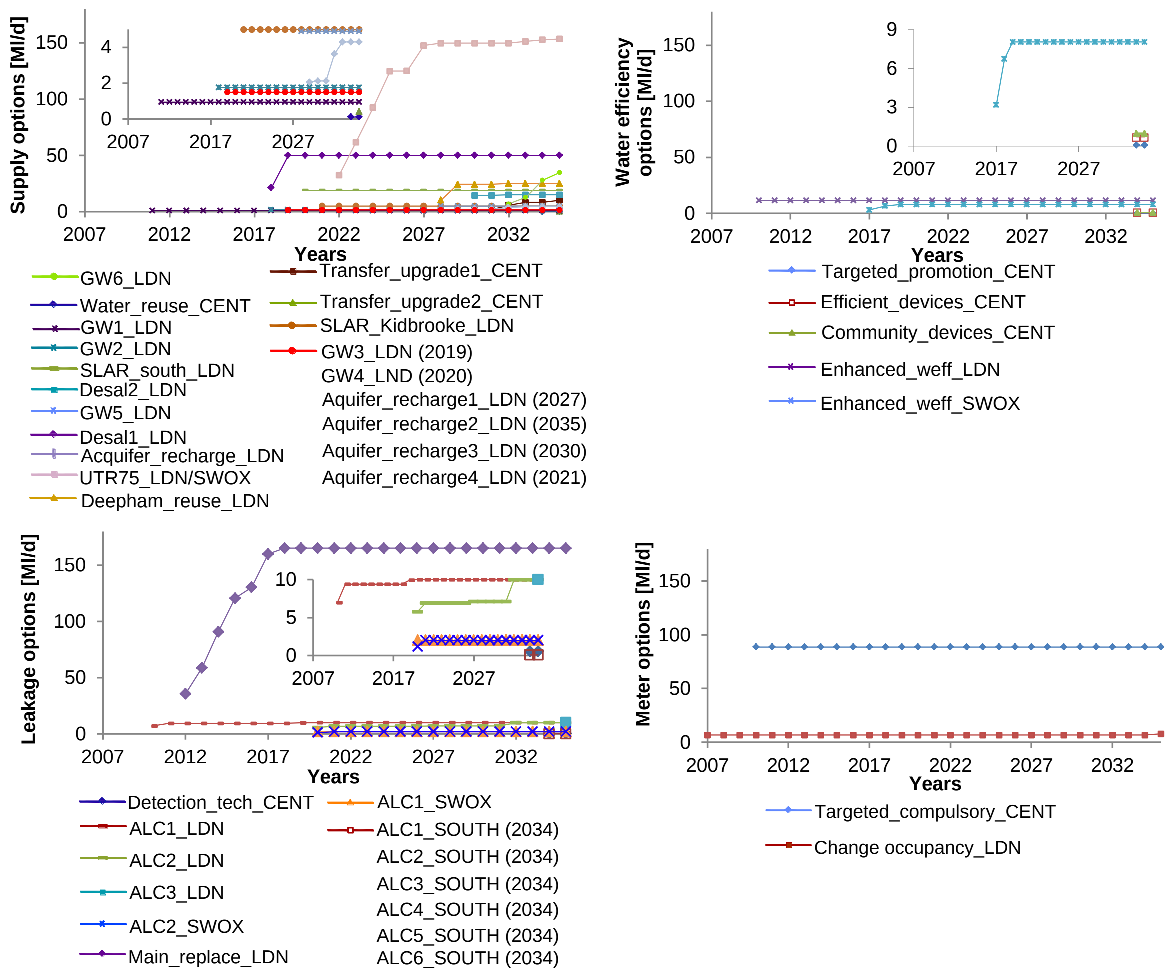

Figure 8.3 Least-cost quantity and scheduling of supply and demand management schemes (metering, water efficiency and leakage reduction) under the DYAA scenario. Results are based on publically available data only and should therefore not be considered a final assessment. The uppercase letters at the end of option codes refer to the WRZ. Options with identical optimal capacities are represented by unique curves. Their activation years are specified in the legend.

Annual capital costs are seen in Figure 8.4 for all supply schemes and the three major types of demand management options (leakage reduction, metering and water efficiency options).

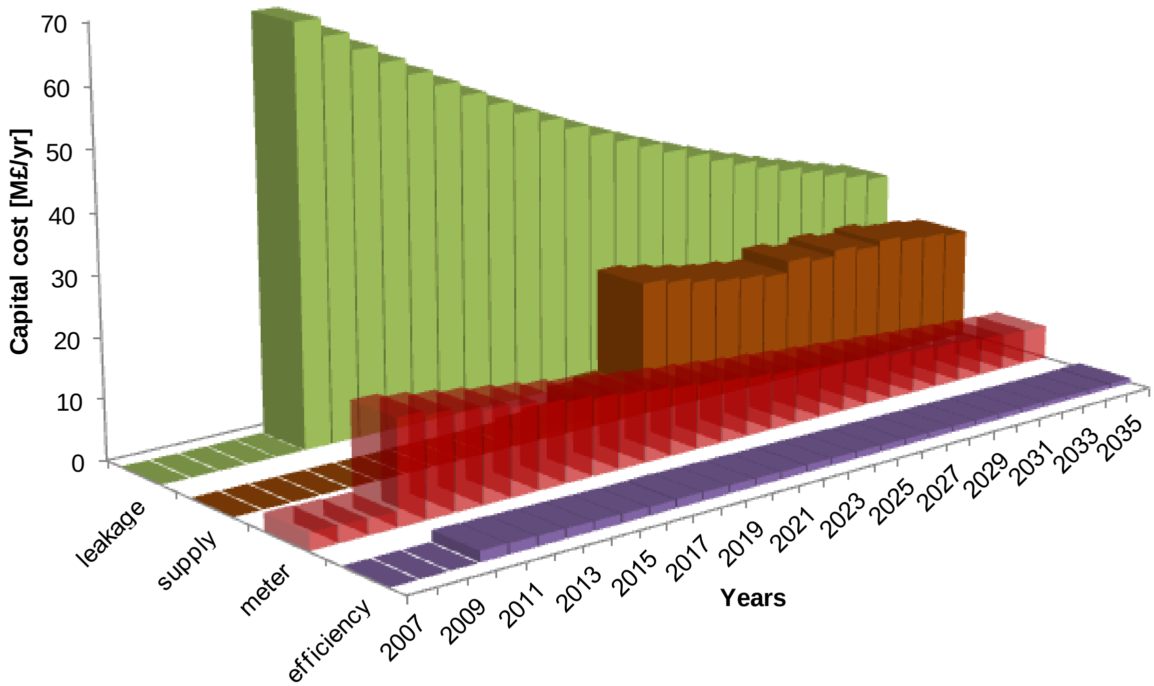

Figure 8.4 Annual capital costs over the planning period for leakage, metering, supply-side and water efficiency options. All costs in millions of pounds are discounted to the base year 2008.

The most prominent investment in the solution is leakage reduction and is primarily a result of the activation of the mains replacement scheme (*Main_replace*) in the London WRZ (This demand option has high CAPEX, but no FOPEX and VOPEX and high benefits (Table 8.1). Other selected leakage options include three out of five levels of ALC in the London WRZ, two out of five levels of ALC in SWOX, fourteen different leakage reduction options in SOUTH, two levels of '*Find&fix*' leakage options in RZ4 and RZ5, a pressure management option in RZ5 and CENT, and a new detection technology scheme (*Detection_tech)* in CENT.

The most capital cost-intensive supply-side options chosen by the model include the UTR (option *RA75*) and the two South London Artificial Recharge Schemes (*SLAR_south* and *SLAR_kidbrooke*) (these are combined into a single option in the RDM implementation).

Water efficiency measures are activated in RZ5, CENT, SOUTH, London and SWOX. Only two metering options are implemented: targeted compulsory metering (TCM) in London and change of occupancy metering (COM) in SWOX.

Figure 8.5 shows the total quantity of water supplied annually by each option type over the planning period whilst Table 8.1 summarises the costs for the supply and DM options.

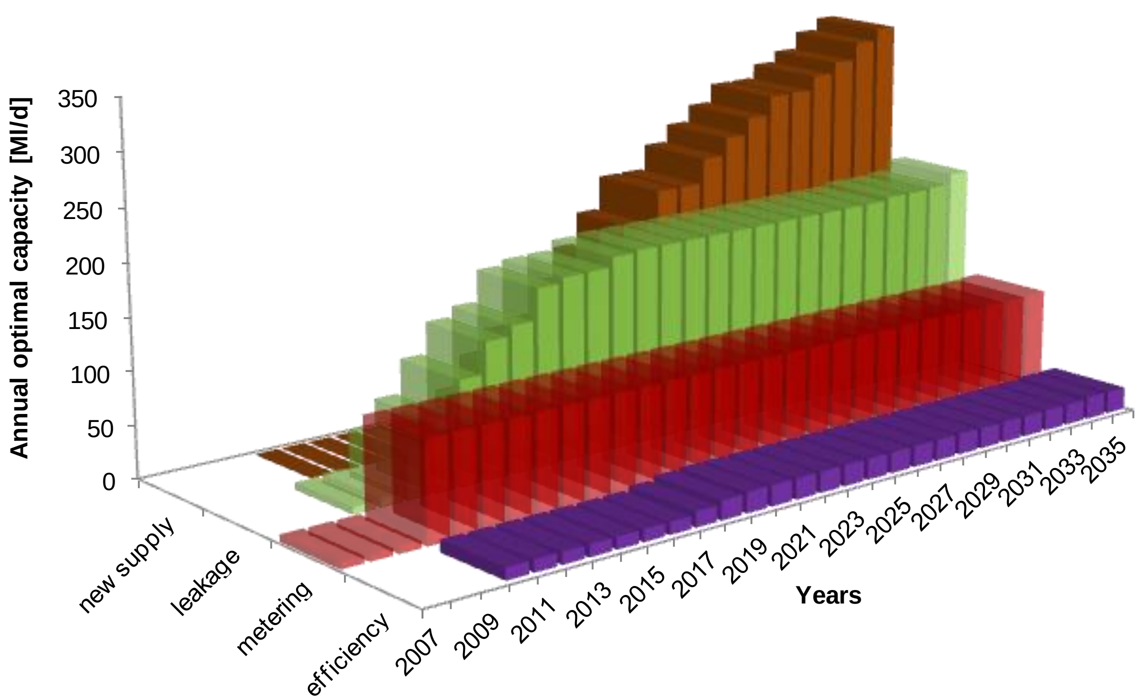

Figure 8.5 Annual optimal capacity over the planning period for leakage, metering, supply-side schemes and water efficiency options under the DYAA scenario.

Table 8.1 Breakdown of costs for new supplies and demand management options. Variable costs are weighted considering a 42 week/year duration for the DYAA scenario and 10 week/year duration for the DYCP scenario.

	Supply options	Leakage Reduction	Metering	Water Efficiency Measures
CAPEX [M£]	290	1044 (1043 resulting from mains replacement in LDN	230 for TCM 48 for COM	31
FOPEX [M£]	29	456	5 for TCM 14 for COM	0.6
Saving, Social & Environmental [M£]	21	-157	-13	-2.4
Weighted VOPEX [M£]	85	42	60 for TCM 14 for COM	0.03

9 Publications arising from this thesis

Matrosov, E.S., 2009. Development of the Interactive River-Aquifer Simulation - 2010 and a comparison of its performance on the Thames basin Technical University of Munich, Munich.

Matrosov, E.S., Harou, J.J., Loucks, D.P., 2011. A computationally efficient open-source water resource system simulator - Application to London and the Thames Basin. Environmental Modelling & Software, 26(12): 1599-1610.

Matrosov, E.S., Huskova, I., Kasprzyk, J.R., Harou, J.J., Reed, P.M. (under review) Many-Objective Optimization and Visual Analytics Reveal Key Planning Trade-offs for London's Water Supply.

Matrosov, E.S., Padula, S., Harou, J.J., 2013. Selecting Portfolios of Water Supply and Demand Management Strategies Under Uncertainty—Contrasting Economic Optimisation and 'Robust Decision Making' Approaches. Water Resour. Manag., 27(4): 1123-1148.

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